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STUDENTS' ACCEPTANCE OF A MOBILE ROBOTIC TRAINING KIT: EXTENDING THE TECHNOLOGY ACCEPTANCE MODEL WITH COGNITIVE LOAD IN VOCATIONAL EDUCATION

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ABSTRACT

Aim/Purpose	This study aims to analyze students' acceptance of mobile robotics training kits in vocational education by extending the Technology Acceptance Model (TAM) through the integration of the cognitive load dimension. This study stems from the limited number of studies that explain the acceptance of robotics learning technology from the perspective of students' cognitive processes.
Background	Although robotics-based learning is increasingly being implemented in engineering and vocational education, most previous research has focused primarily on psychological, social, and technological factors in explaining technology acceptance. This study addresses this gap by integrating Cognitive Load Theory into the Technology Acceptance Model to explain how intrinsic, extraneous, and germane cognitive load influence the perceived usefulness and perceived ease of use of a mobile robotic training kit.
Methodology	This study employed a quantitative approach using Partial Least Squares Structural Equation Modeling (PLS-SEM). The study participants consisted of 118

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students from the Industrial Electronics Technology program. Data were collected using a 26-item Likert-scale questionnaire measuring intrinsic cognitive load, extraneous cognitive load, germane cognitive load, perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention.

Contribution This study significantly expands the TAM model by integrating CLT as a cognitive mechanism that explains how perceptions of ease of use and usefulness of mobile robotics training kits are formed during learning robotics, microcontrollers, or complex embedded systems. The study reveals that cognitive load is not merely an additional factor but a key determinant of technology acceptance in the learning process.

Findings The results indicate that nine out of ten hypotheses were supported. Extraneous and germane cognitive load significantly influenced perceived usefulness and perceived ease of use, while intrinsic cognitive load affected perceived usefulness but not perceived ease of use. Furthermore, perceived usefulness and perceived ease of use significantly influenced attitude toward using ($R^2 = 0.676$), and attitude toward using had a very strong effect on behavioral intention ($R^2 = 0.614$). These findings demonstrate that the interplay between cognitive load and perceptions of technology shapes students' acceptance of the mobile robotic training kit.

Recommendations for Practitioners Teachers and educational media developers need to design robotics training kits that are structured, intuitive, and aligned with vocational competencies to reduce unnecessary cognitive load and enhance perceptions of ease of use and utility. Learning should also be structured progressively, moving from basic concepts to more complex projects, so that students can use the technology more effectively.

Recommendations for Researchers Future researchers are encouraged to continue developing models of educational technology acceptance by simultaneously incorporating cognitive, pedagogical, and other individual factors. Additionally, further studies could compare this model with other learning technologies or across different educational levels to broaden the generalizability of the findings.

Impact on Society The findings of this study have significant implications for educators regarding the design of mobile robot training kits that take cognitive load into account, particularly by reducing unnecessary cognitive load through simplified interfaces, integrated representations, and the elimination of redundant information, while optimizing relevant cognitive load through scaffolding, guided exploration, and repetitive problem-solving tasks. The application of a systematic learning framework, ranging from foundational knowledge to the integration of complex systems, is crucial for supporting students' understanding and thereby enhancing perceived ease of use, perceived usefulness, and, ultimately, students' acceptance of robotics technology in vocational education.

Future Research Given the limitations of this study, the researcher offers several recommendations for future research. First, this model needs to be tested on a larger and more diverse sample with similar learning characteristics, such as robotics, microcontrollers, or embedded systems, at the vocational high school level. Second, the model should be expanded to include other pedagogical, individual, and technological variables to gain a more comprehensive understanding of the assessment of the acceptance of mobile robotic training kits in vocational education.

Keywords mobile robotic training kit, technology acceptance model, cognitive load, vocational education, robotics learning

INTRODUCTION

The rapid development of robotics and industrial automation systems in the era of the Fourth Industrial Revolution has made robotics a key component in improving industrial efficiency and productivity (Ellithy et al., 2024; Tantawi et al., 2025). The impact of this development requires vocational education to continuously adapt its curriculum, learning technologies, and instructional models to align with industry needs (Ariansyah et al., 2024; Rikala et al., 2024; Sukardi et al., 2024). Thus, learning using robotics systems has become a crucial approach in developing students' technical competencies through authentic learning experiences involving sensors, actuators, control systems, and programming that reflect real-world industrial applications (Chookaew et al., 2021; Setyawan, Sukardi, Risfendra, Tri Putra Yanto, & Tze Kiong, 2025). However, the main issues that arise are technological limitations and learning approaches, as well as technology acceptance models that have not yet fully explained how students understand, use, and accept complex robotics technology.

Several researchers have pursued the development of robotics technology in education in the past; platforms such as LEGO Mindstorms, mBot, and ReFiBot have been shown to enhance students' knowledge, programming skills, as well as their motivation and engagement in learning (Antunes et al., 2023; Díaz-Lauzurica & Moreno-Salinas, 2023; Guerrero-Osuna et al., 2023; Pantos et al., 2023; Selcuk et al., 2024), yet its implementation in vocational education still faces fundamental limitations. These platforms generally focus on block-based programming and off-the-shelf systems, thus lacking support for modular flexibility and failing to fully align with industry demands that require mastery of low-level programming languages such as C/C++ and comprehensive system integration. Consequently, learning tends to be limited to developing basic logic and programming skills, without fostering deep technical literacy. However, in the context of vocational education, students are required to master more comprehensive competencies, including electronic circuit design, electrical system integration, and the development of embedded control systems to build complete robotic systems (Boya-Lara et al., 2022; Pekarcikova et al., 2025; Setyawan, Sukardi, Risfendra, Tee, et al., 2025). This gap indicates that existing robotics learning technologies are not yet fully capable of meeting the needs of vocational education, which demands a holistic mastery of robotic systems.

Given the limitations of previous research, the novelty of this study also lies in the development of a modular mobile robot training kit designed to support holistic learning, from basic concepts to system applications. By using this training kit, students can independently understand pin configurations, build electronic systems, and develop microcontroller-based solutions in the form of mobile robots, thereby not only using the systems but also comprehensively building them. By emphasizing a flexible design, this platform can be used across various skill levels, from beginners to experts, and supports the implementation of diverse robotics applications, such as line-following robots, wall-following robots, and smartphone-controlled robots. Thus, this training kit is not only relevant to project-based learning but also effective in fostering students' conceptual understanding and technical skills continuously throughout the learning cycle in vocational education.

Previous researchers have also examined various factors influencing the acceptance of robotics technology in vocational education, such as technology anxiety, task quality, perceived adaptability, and enjoyment of using the technology (S. Chen et al., 2023; Di Battista et al., 2023). Other studies have also expanded the technology acceptance framework by incorporating variables such as risk perception, subjective norms, and individual characteristics, including self-efficacy and novelty seeking (X. Chen et al., 2025; Lei et al., 2022). Although the results of these studies make valuable contributions, the assessment approaches used are still dominated by psychological and social perspectives and have not explicitly examined the cognitive mechanisms underlying students' interactions with robotics learning technology. Meanwhile, in complex robotics learning (programming, electronic circuits, sensors, and actuators), cognitive processes play a key role in shaping students' understanding, use, and acceptance of technology (Boya-Lara et al., 2022; Souza et al., 2021)

This limitation highlights a conceptual gap in the Technology Acceptance Model (TAM) literature, particularly in the context of complex technology-based learning. The TAM model traditionally emphasizes the roles of perceived ease of use and perceived usefulness in shaping attitudes and intentions toward technology use, but has not explicitly accounted for the cognitive load users experience when interacting with technology (Davis, 1993). Consequently, the TAM's ability to explain technology acceptance in learning environments that demand high cognitive processing, such as robotics, is limited. Thus, the objective of this study is to develop and test a model of technology acceptance in robotics by integrating cognitive load theory (CLT) into the Technology Acceptance Model (TAM), to explain how the dimensions of intrinsic, extraneous, and germane cognitive load influence the perceived ease of use and perceived usefulness of the developed robotics technology.

THEORETICAL FRAMEWORK

MOBILE ROBOTIC TRAINING KIT

A mobile robotics training kit is a learning tool used to teach robotics or embedded control systems at vocational schools, as it uses a microcontroller as its controller. Conceptually, the mobile robotics training kit serves as a bridge between theoretical concepts and technical practice through authentic experimental activities, programming, and problem-solving. The development of the mobile robotic training kit is also strongly supported by constructivist learning theory; using this kit in the learning process enables students to build conceptual understanding through direct experience, starting from the process of designing, testing, and refining robotic systems (Alam & Mohanty, 2024). Additionally, the mobile robotic training kit supports a learning-by-doing approach, emphasizing that conceptual understanding develops through the transformation of concrete experiences into knowledge through a cycle of exploration, reflection, conceptualization, and active experimentation (Bertacchini et al., 2022; Coufal, 2022). Through this learning process, students can connect theoretical concepts they have learned with technical practice, develop systematic thinking skills, and improve problem-solving skills in designing a robotic system (Setyawan, Sukardi, Risfendra, Tee, et al., 2025).

The mobile robot training kit is designed as an integrated learning tool that combines hardware components with software to support the comprehensive development of robotics systems. Through hands-on interaction, students learn core robotics concepts such as sensor integration, programming algorithms, navigation systems, and microcontroller programming in an applied learning environment. These concepts constitute the core competencies that students must master in robotics system learning (Boya-Lara et al., 2022; Kanamura et al., 2021; Raudmäe et al., 2023). Through this design, the developed training kit can bridge the gap between conceptual understanding and technical practice in robotics education within vocational education (Alam & Mohanty, 2024). Therefore, the use of this kit not only facilitates experimentation but also encourages iterative system design and problem-solving, which are crucial for strengthening students' technical competencies.

The adoption of robotics learning technology in vocational education focuses on a more authentic, integrated, and industry-oriented learning approach. This approach is driven by the growing need for competencies encompassing device integration, control systems, industrial machine automation, and complex problem-solving as the foundations of Industry 4.0 (de Souza & Debs, 2024; Supriya et al., 2024). Consequently, various vocational education institutions have adopted project-based learning and robotics platforms that realistically simulate industrial conditions to enhance graduates' work-readiness (Phokoye et al., 2024; Setyawan et al., 2026). However, the increasing complexity of the technology and learning materials being implemented also has the potential to raise cognitive demands on students, as they must simultaneously integrate knowledge of programming, electronics, embedded systems, and decision-making to solve real-world problems (Huang et al., 2025). Thus, the success of implementing robotics technology in vocational education is determined not only by the sophistication of the technology used but also by the quality of instructional design that supports cognitive processes and develops technical competencies relevant to the needs of modern industry.

The Influence of Mobile Robotics Training Kits on Students' Cognitive Load

The use of mobile robotic training kits in the learning process in vocational education significantly affects students' cognitive load: if the training kit is designed to facilitate student learning, it will reduce cognitive load; conversely, if it is not, it will increase it. Cognitive load itself emphasizes that effective learning depends on the learning system's ability to manage the cognitive load students experience as they understand new information. The system itself includes learning technologies used to convey information to students (Ibrahim et al., 2025; Meng et al., 2025). Robotics education involves complex learning because it encompasses a range of scientific concepts, including electronics, embedded systems, programming, mechanics, and control systems (Boya-Lara et al., 2022; Kanamura et al., 2021; Raudmäe et al., 2023). This complexity can increase intrinsic cognitive load, the cognitive burden arising from the complexity of the material being studied (Le Cunff et al., 2024; Meng et al., 2025). Therefore, the design of an appropriate training kit is a critical factor in ensuring that students can process information effectively without experiencing excessive cognitive load that could hinder learning.

In the design of educational technology, four factors influence students' cognitive load: technological complexity, interface design, instructional design, and the quality of the educational technology. Thus, the mobile robot training kit has the potential to be a primary source of students' cognitive load due to its technological complexity. This complexity is reflected in the interactivity element of the training kit, namely the extent to which students must simultaneously integrate various elements in the robotics system, such as programming, circuits, and control system algorithms, into a single unit (O. Chen et al., 2023; Sweller, 2023). The greater the complexity of these elements, the greater the demand for information processing in working memory, particularly for students who lack a solid foundation (Gorbunova et al., 2025). Thus, a mobile robot training kit's design not only determines the depth of the material students learn but also directly influences students' intrinsic cognitive load through the complexity of the system being built. Therefore, learning technology must be designed in accordance with students' cognitive readiness levels to avoid causing cognitive overload and to continue supporting an optimal learning process.

The instructional design and quality of the training kit are also key factors influencing students' cognitive load. This load stems from how information and interactions within the training kit are presented to students. Factors such as the clarity of the training kit interface, the structure of learning modules, and the integration between hardware and software are crucial in directing students' cognitive attention to relevant aspects (O. Chen et al., 2023; Skulmowski & Xu, 2022). Thus, an unstructured training kit design, fragmented instructions, or disjointed information have the potential to increase students' cognitive load, thereby disrupting the efficiency of information processing in working memory. Consequently, the quality of training kit design is not merely technical but also determines the extent to which extraneous cognitive load can be minimized to support effective and focused learning processes (Wang et al., 2025).

Through designs that explicitly guide students' cognitive activities in the formation and consolidation of knowledge, we can also facilitate appropriate cognitive load. Cognitive load does not depend solely on the complexity of the material, but also on the extent to which the training kit is designed to promote meaningful cognitive engagement through scaffolding, guided exploration, and authentic problem-solving (Candido & Cattaneo, 2025; Sweller et al., 2019). Through a modular design integrated with project-based tasks, and through students' active involvement in the system design and testing process, cognitive resources can be optimally allocated to knowledge construction (Faber et al., 2024). Thus, the design of the training kit serves not only as a practical tool but as a strategic learning resource that directs cognitive processing toward deep learning, thereby enhancing the efficiency of schema formation and knowledge transfer in students' robotics learning (Sweller, 2023).

Cognitive Load Theory

Cognitive Load Theory (CLT) is the most influential theoretical framework in educational psychology and instructional design because it explains how the limitations of human cognitive architecture determine the effectiveness of the learning process. Fundamentally, this theory explains that new information acquired by students is first processed through working memory, which has limited capacity and duration; subsequently, if this information is successfully understood and well-organized by the student, it can be stored in long-term memory in the form of schemas that can be retrieved to support performance and problem-solving (Sweller, 1988; Zeitlhofer et al., 2024). Working memory is limited in both capacity and duration; when these limits are exceeded, cognitive load occurs, affecting students' ability to process and understand information (Kalyuga & Singh, 2016; Zeitlhofer et al., 2024). Thus, learning is not merely about improving short-term learning outcomes, but a process that equips students to acquire schemas that help them identify patterns, group information elements, and reduce cognitive processing demands on subsequent tasks (Candido & Cattaneo, 2025; Sweller, 1988).

Sweller (1988, 1994, 2010) asserts that task completion does not merely determine effective learning, but rather the extent to which the designed learning process supports the formation and automation of schemas in long-term memory. Within the CLT framework, schemas organize numerous pieces of information into meaningful units, enabling them to be processed more efficiently. Meanwhile, schema automation reduces demands on working memory during complex tasks (Quintero-Manes & Vieira, 2025). The cognitive difficulty of a subject can be explained through the element of interactivity; that is, the extent to which information elements must be processed simultaneously to facilitate student understanding. Materials with high interactivity, such as programming, microcontrollers, and robotics, require the simultaneous integration of many elements, potentially leading to higher cognitive load (Candido & Cattaneo, 2025; X. Chen et al., 2025; Quintero-Manes & Vieira, 2025). A strategy to address this cognitive load is to first train students through foundational learning before engaging in complex learning. Acquiring prerequisite knowledge before beginning primary learning tasks can reduce cognitive demands during learning and enable students to allocate memory resources more effectively to new information (Lawson & Mayer, 2025; Sweller, 2024).

Within the CLT framework, there are three categories of cognitive load: intrinsic, extraneous, and germane (Sweller, 2010). Intrinsic cognitive load (ICL) reflects the mental demands arising from the inherent complexity of a task and the interactions among elements processed simultaneously. When this complexity exceeds the student's existing knowledge schema, working memory capacity becomes overloaded, leading to difficulties in understanding, operating, and completing the assigned task (O. Chen et al., 2023; Sweller, 2023). Consequently, this condition directly reduces perceived ease of use, as technology is perceived as requiring greater effort to learn and use. Low perceived ease of use of learning technology can limit students' ability to explore and use its functions optimally, thereby making the learning benefits offered by the technology less apparent (Ma, 2025; Maričić et al., 2025). Based on this condition, high ICL tends to reduce the perceived ease of use and perceived usefulness of the technology, as excessive cognitive complexity hinders students' access to the true instructional value of the learning technology. Thus, the relationship between ICL and technology acceptance occurs through perceptions of ease of use and usefulness, where increased cognitive demands can reduce positive evaluations of the technology's use (Dou et al., 2026). Based on this hypothesis development, the researchers formulate the following hypotheses:

- **H1:** The intrinsic cognitive load of the mobile robotic training kit has a significant effect on the perceived usefulness of the mobile robotic training kit.
- **H2:** The intrinsic cognitive load of the mobile robotic training kit has a significant effect on the perceived ease of use of the mobile robotic training kit.

Furthermore, extraneous cognitive load (ECL) arises from suboptimal technological and instructional design, such as non-intuitive interfaces, fragmented information, complex navigation, and a lack of integration between information representation and learning activities (Sweller, 2023). High levels of ECL in the use of learning technology can divert students' cognitive resources from relevant learning processes toward activities that do not directly contribute to knowledge formation. Consequently, students must expend additional mental effort merely to understand how to use the system, leading them to perceive the technology as more difficult to learn and operate (O. Chen et al., 2023). This situation directly reduces perceived ease of use because students view interacting with technology as requiring excessive effort. Furthermore, when irrelevant activities occupy a significant portion of working memory capacity, students are less able to utilize the technology's features and functions optimally, ultimately reducing perceived usefulness (Dou et al., 2026; Ma, 2025; Maričić et al., 2025). Thus, the greater the ECL induced by the training kit design, the lower students' perceived ease of use and perceived usefulness. Cognitive load stemming from interface design, information architecture, and system characteristics negatively impacts perceptions of usefulness and ease of use, making it a critical factor determining the success of educational technology adoption (Ngo, 2026). Based on this hypothesis development, the researchers formulate the following hypotheses:

H3: The extraneous cognitive load of the mobile robotic training kit has a significant effect on the perceived usefulness of the mobile robotic training kit.

H4: The extraneous cognitive load of the mobile robotic training kit has a significant effect on the perceived ease of use of the mobile robotic training kit.

Finally, extraneous cognitive load (ECL) is the cognitive load resulting from the investment of cognitive resources in the construction, organization, and automation of knowledge schemas. In robotics learning, GCL emerges when a mobile robotic training kit is designed to promote meaningful cognitive engagement through scaffolding, guided exploration, and project-based tasks. This design facilitates the integration of concepts, procedures, and real-world applications, thereby reducing uncertainty in technology use and enhancing information processing efficiency (O. Chen et al., 2023; Sweller, 2023). Increased GCL in learning can strengthen perceived ease of use because students have more structured schemas for understanding and operating the technology. Furthermore, when technology effectively supports knowledge formation and successful task completion, students will be better able to recognize the instructional benefits, thereby increasing perceived usefulness (Dou et al., 2026; Maričić et al., 2025). Thus, GCL not only contributes to the quality of learning but also serves as a cognitive mechanism that bridges meaningful learning experiences with the formation of positive perceptions regarding the ease and usefulness of technology. This concept is reinforced by the findings of Huang et al. (2025) and Ngo (2026), which show that GCL significantly influences perceived ease of use and perceived usefulness, thereby increasing technology acceptance by strengthening users' perceptions of the learning system's value and ease of use. Based on this hypothesis development, the researcher formulates the following hypothesis:

H5: The germane cognitive load with the mobile robotic training kit has a significant effect on the perceived usefulness of the mobile robotic training kit.

H6: The germane cognitive load with the mobile robotic training kit has a significant effect on the perceived ease of use of the mobile robotic training kit.

TECHNOLOGY ACCEPTANCE MODEL

The Technology Acceptance Model (TAM) is a theory introduced by Fred D. Davis in 1986 that provides a theoretical framework explaining why individuals accept or reject a technology (W. Li et al., 2024). In its initial theoretical framework, TAM emphasizes that two main cognitive factors determine technology acceptance: Perceived Usefulness (PU) and Perceived Ease of Use (PEU) (Davis, 1993). PU is the degree to which an individual believes that using a technology will improve their performance. Meanwhile, PEU refers to an individual's level of confidence that the technology can be used with minimal effort. These two constructs influence Attitude Toward Using (ATU) and Behavioural Intention (BI) to actually use the technology (Davis, 1989). Additionally, the TAM framework allows other researchers to integrate external variables that may drive technology adoption (Al-Adwan et al., 2023). Currently, the TAM theoretical framework is viewed not only as a predictive model but also as an epistemological framework for understanding the relationship between system characteristics, user perceptions, and the decision to adopt technology (N. Ali et al., 2023; Sánchez-Prieto et al., 2020).

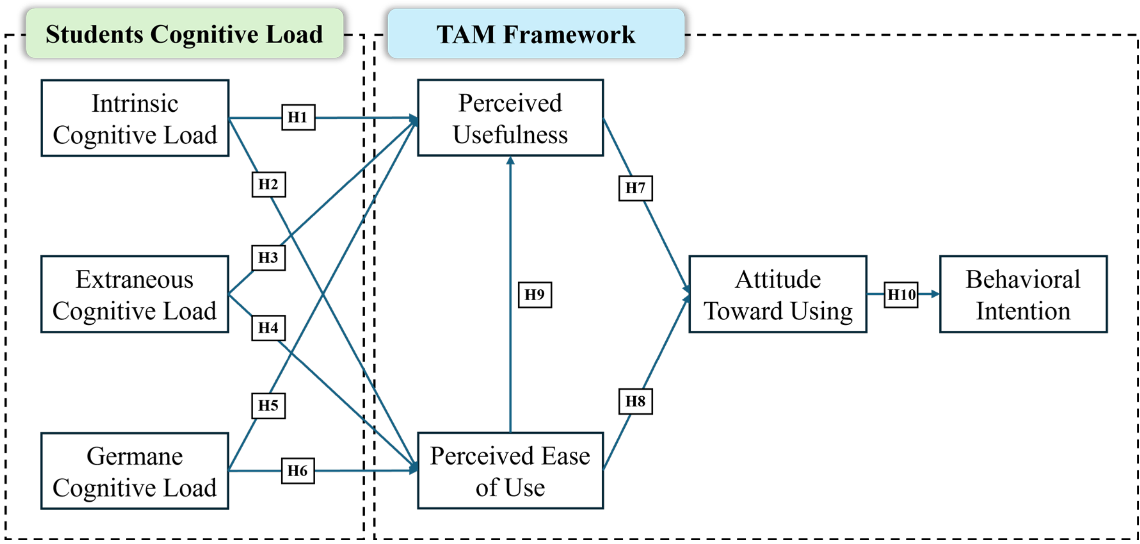

Figure 1. Theoretical framework for assessing the acceptance of a mobile robotic training kit using the Technology Acceptance Model extended with cognitive load

Within the TAM framework, PEU is viewed as the belief that technology can be used without excessive effort, whereas PU is the belief that technology can enhance user performance. Theoretically, easier-to-use technology allows users to focus more on the system's functional benefits, thereby increasing perceived usefulness (Zobeidi et al., 2023). Additionally, the ATU reflects the extent to which an individual holds a positive or negative evaluation of the system's use. Consequently, users tend to form a more positive attitude toward easy-to-use technology (PEU) because such technology reduces frustration, confusion, and psychological resistance during the interaction process (W. Li et al., 2024). In the TAM, PU also plays a crucial role in shaping ATU, as attitudes toward usage are influenced not only by how easy a technology is to use but also by the extent to which it is perceived to provide tangible benefits to users. An individual is likely to develop a positive evaluation of a technology if they believe it can improve the quality, effectiveness, or efficiency of task completion (W. Li et al., 2024).

Additionally, ATU serves as a psychological mediator between cognitive beliefs and behavioural intentions. Here, ATU reflects the user's overall evaluation of the act of using technology – whether the act is perceived as positive, enjoyable, valuable, or the opposite. When students perceive technology use as beneficial, useful, and advantageous, their tendency to adopt it increases (Sánchez-Prieto et al., 2020). This conceptual relationship is further supported by empirical evidence regarding the evaluation of robotic technology in the learning process (S. Chen et al., 2023; X. Chen et al., 2025; Di Battista et al., 2023; Lei et al., 2022). Based on the development of this hypothesis, the formulated hypothesis is as follows:

H7: Perceived Usefulness of the Mobile Robotic Training Kit has a significant effect on Attitude Toward Using the Mobile Robotic Training Kit.

H8: Perceived Ease of Use of the Mobile Robotic Training Kit has a significant effect on Attitude Toward Using the Mobile Robotic Training Kit.

H9: Perceived Ease of Use of the Mobile Robotic Training Kit has a significant effect on Perceived Usefulness of the Mobile Robotic Training Kit.

H10: Attitude Toward Using the Mobile Robotic Training Kit has a significant effect on Behavioural Intention to Use the Mobile Robotic Training Kit.

Based on the theoretical foundations of CLT and TAM, the researcher developed a hypothetical model that integrates students' CLT dimensions with TAM's technology acceptance mechanisms (Figure 1) to test the relationships and hypotheses among the variables proposed in this study. The integration of TAM and CLT is a fundamental conceptual necessity, not merely a methodological choice, in explaining technology acceptance in complex learning environments such as robotics. The TAM framework traditionally focuses on the perceptual constructs PEU and PU without explicitly specifying the cognitive mechanisms underlying their formation. Meanwhile, CLT provides a robust framework for explaining how cognitive load influences information processing in working memory, but it does not directly link this to technology adoption decisions. In robotics learning that utilizes complex technology, students evaluate it not only on subjective perceptions but also on their cognitive capacity to process its complexity. Thus, without the integration of CLT, TAM risks oversimplifying the technology acceptance process, while without TAM, CLT cannot explain the cognitive implications for students' technology adoption behavior. Thus, integrating these two theories is necessary to build a more comprehensive model capable of explaining how cognitive factors causally shape perceptions of ease and usefulness and, ultimately, determine technology acceptance in learning.

METHODOLOGY

RESEARCH PROCEDURE

This study was conducted over a full semester, comprising 16 sessions, by integrating a mobile robotics training kit into the Industrial Electronics Engineering program at a vocational high school. The learning was designed using a project-based approach comprising six learning steps: determining learning objectives, learning and training basic concepts, planning projects, presenting and evaluating designs, implementing projects, and presenting and evaluating projects. The learning materials used during the learning process can be accessed via the following links: https://doi.org/10.5281/zenodo.18503667 for the learning module, and https://doi.org/10.5281/zenodo.18820746 for the worksheet for systematically conducting practical exercises using the mobile robotic training kit. It is hoped that this process will provide a practical, collaborative, and problem-solving-based learning experience (Nannim et al., 2025; Setyawan, Sukardi, Risfendra, Tee, et al., 2025). The integration of the mobile robotic training kit into this learning process aims to provide students with hands-on experience with robotic technology, enabling them to evaluate their perceptions of perceived ease of use, perceived usefulness, attitude toward technology use, and behavioral intention, as described in the TAM framework. Additionally, this study examines students' cognitive load while using the mobile robotic training kit during project-based learning activities.

During the first session, students were introduced to a mobile robotics training kit comprising a microcontroller, ultrasonic sensors, DC motors, and a robot control system. The teacher explained the function of each component and how the mobile robot system used in the practical activities works. This stage aimed to build students' initial understanding of basic robotics concepts and to prepare them for the project-based learning process. Starting in the second week, project-based learning steps are implemented, beginning with defining learning objectives, followed by instruction and training on the basic concepts of robotics. In this phase, learning is still heavily guided by the teacher, covering hardware, circuits, and microcontroller programming, so that students have foundational knowledge before undertaking the project. In this phase, the training kit is used in basic learning mode (Figure 2d). Learning and training in basic concepts are essential for vocational students and critical to the success of a project, particularly for those still at the beginner stage (Hmelo-Silver et al., 2007; Kirschner et al., 2006). Providing structured instruction in the form of basic concept training before a project begins can improve the quality of technical solutions and reduce conceptual errors during project implementation (Berselli et al., 2020; Savary, 2006). This introductory course runs through session 8.

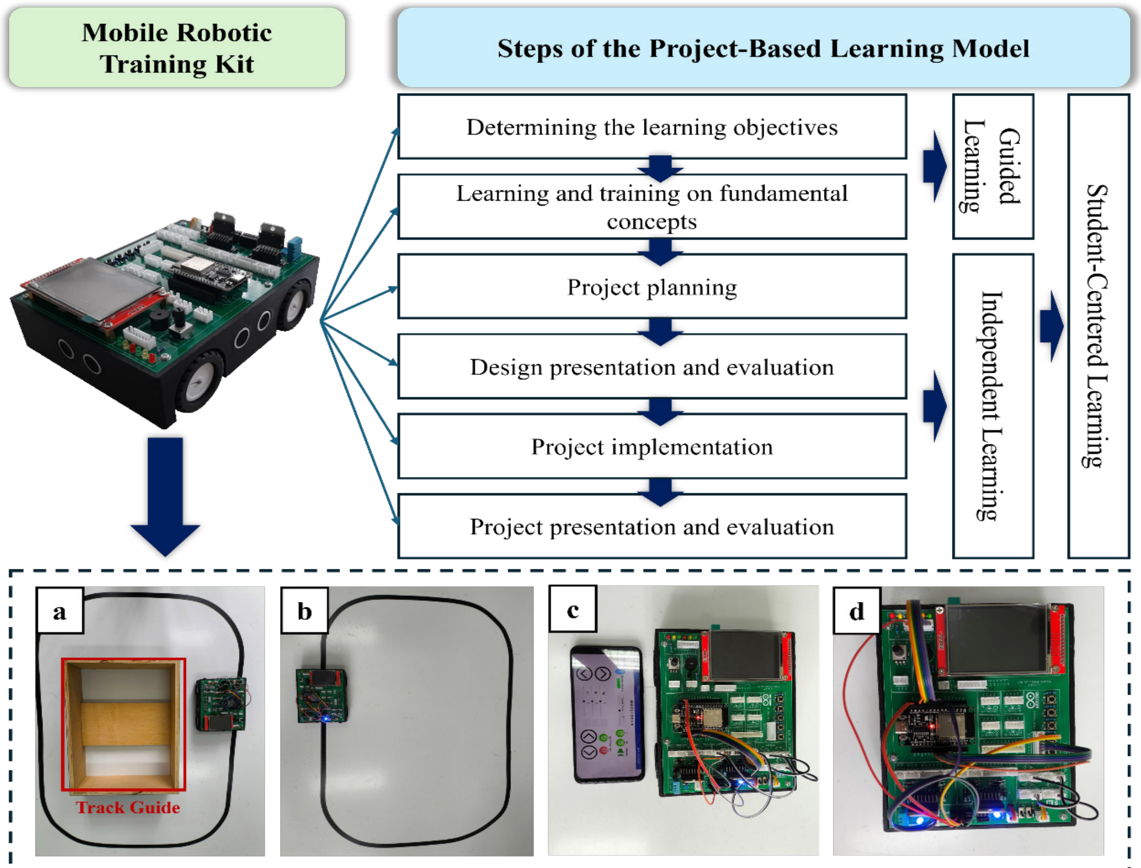

Figure 2. The learning concept using a mobile robotic training kit: (a) wall-following robot, (b) line-following robot, (c) smartphone-controlled robot, and (d) basic learning module

In sessions 9 and 10, students planned a robotics project by designing a robotic system developed using a training kit. This design process included the electronic circuitry and robot programming. For their projects, students could choose from three application modes: a wall-following robot (Figure 2a), a line-following robot (Figure 2b), or a smartphone-controlled robot (Figure 2c). In Week 11, students presented the results of their electronic circuit and programming designs, during which the teacher provided feedback on the design's feasibility and potential improvements before the project was implemented. This phase enables students to develop critical thinking skills, system planning, and problem-solving abilities in the development of robotics technology (R. C. Hsu & Tsai, 2022; Hussain et al., 2022). Subsequently, during sessions 12 through 15, the project implementation phase takes place, where students begin working on the project by assembling robot components, connecting sensors and actuators, and programming the robot system using a mobile robotics training kit.

After the project was completed, during the 16th session, the students gave presentations, and the teacher evaluated the projects they had worked on. At this stage, the students demonstrated the robots they had built and explained the design and construction processes they had followed. This entire series of activities provided a hands-on learning experience and enabled students to acquire knowledge, skills, and experience in using robotics technology. The learning process carried out during the lessons is shown in Figure 3. After the 16 learning sessions were completed, students were asked to complete a research questionnaire based on constructs in the TAM, which had been expanded to include the cognitive load variable. The questionnaire data were analyzed to identify the factors influencing students' acceptance of mobile robotic training kits in vocational education. In short, these learning activities are shown in Table 1.

Figure 3. Learning activities during the learning process at (a) SMK Negeri 5 Padang, (b) SMK Negeri 1 Sumatera Barat, and (c) SMK Teknologi Robotik UNP

Table 1. Learning activities conducted during the study

Weeks/ sessions	Learning phases	Activity descriptions
1	Determining the learning objectives	Introduction to the training kit, components, and robot systems; setting learning objectives and outcomes for students
2 to 8	Learning and training on fundamental concepts	Guided instruction on basic concepts (hardware, circuits, programming)
9 to 10	Project planning	Designing robot systems (circuits & programs); selecting robot types
11	Design presentation and evaluation	Presentation of designs and feedback from the teacher
12 to 15	Project implementation	Assembly, component integration, and robot programming
16	Project presentation and evaluation	Demonstration of project results and evaluation
17	Data collection	Completion of questionnaires (TAM + Cognitive Load)

PARTICIPANTS

The participants in this study were 11th-grade students (second-year students in a three-year program) majoring in industrial electronics engineering at vocational high schools in Sumatera Barat Province, Indonesia, with a total of 118 students. This research process was authorized by the principals of the respective vocational high schools and approved by the Head of the West Sumatra Provincial Education Office under letter number 000.9/5921/PSMK/DISDIK-2025. Furthermore, the sample selection used to determine the research respondents employed a purposive sampling technique, taking into account the specific characteristics of the respondents, namely, students with direct experience using mobile robotic training kits in project-based learning, ensuring the data collected is more relevant to the phenomenon under study. This approach allows for a more in-depth analysis of cognitive mechanisms and technology acceptance, as it involves only participants who truly represent the context of complex and authentic technology use (Campbell et al., 2020). Thus, all 118 students served as respondents in this study, with the following demographic characteristics: 83 male students (70.34%) and 35 female students (29.66%), 14 students aged 16 (11.86%), 96 students aged 17 to 18 (81.36%), and 8 students aged 19 (6.78%). All participating students completed learning activities using a mobile robot training kit, gaining direct experience with this learning medium.

Research Data Collection Instrument

The development of the TAM assessment instrument adapts the key guidelines in Davis (1989) as the conceptual framework for TAM. It draws upon instruments developed by N. Ali et al. (2023), W. Li et al. (2024), and Sánchez-Prieto et al. (2020) to assess AI and robotics technologies in learning. The TAM assessment variables developed have been empirically validated and proven reliable for measuring technology acceptance in learning. Following the development phase, the TAM instrument used in this study consists of four TAM assessment variables: Perceived Usefulness (4 items), Perceived Ease of Use (4 items), Attitude Toward Use (4 items), and Behavioral Intention (3 items). These are detailed in Appendix A.

Furthermore, the development of an instrument to assess students' cognitive load adopted the key guidelines from Sweller (2024), who developed the cognitive load theory, and drew upon instruments developed by O. Chen et al. (2023), Leppink et al. (2013), and Quintero-Manes and Vieira (2025) to assess students' cognitive load regarding multimedia learning materials and computer programming. This developed instrument has been empirically proven to be valid and reliable for measuring students' cognitive load. Following the development of the instrument, there are three variables for assessing cognitive load: intrinsic cognitive load (4 items), relevant cognitive load (4 items), and external cognitive load (3 items), as specifically detailed in Appendix A. Overall, both the TAM and CLT assessments were evaluated using a Likert scale consisting of 5 response options ranging from 1 (strongly disagree) to 5 (strongly agree) (Sullivan & Artino, 2013).

During the instrument development process, the researchers conducted a content validity analysis of the developed instrument before using it in the study. The instrument was evaluated by two experts in the fields of vocational education assessment and robotics education. The experts evaluated each assessment item developed for alignment with the constructs being assessed and for grammatical structure, providing comments and suggestions to improve the instrument (Guo et al., 2025). Based on the constructive feedback from these experts, the researcher revised the developed instrument. First, the researcher corrected the use of standard terminology and spelling in the assessment items. Second, the assessment items were refined to focus directly on the robotics learning activities being conducted. Finally, the researchers made the statements more concise and direct to the point. These points were revised based on the experts' evaluations, resulting in 26 assessment items for TAM and CLT, as shown in Appendix A.

Data Analysis Techniques

The data analysis technique used in this study employs the Partial Least Squares - Structural Equation Modeling (PLS-SEM) approach, using SmartPLS software to analyze relationships among variables within the research model. The PLS-SEM approach was chosen because it can comprehensively analyze the simultaneous relationships among latent variables and their indicators, and it is widely used in research on the acceptance of educational technology (Hair et al., 2021; Thakkar, 2020). Data analysis in this study began with an evaluation of the measurement models using reflective analysis (convergent and discriminant validity and reliability) and formative analysis (collinearity). Convergent validity was evaluated using the Average Variance Extracted (AVE), which must be greater than 0.50, and the outer loadings, where each indicator is expected to have a loading greater than 0.70. Meanwhile, discriminant validity was tested using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), with values> 0.90 indicating discriminant validity (Henseler et al., 2015). Next, construct reliability was tested using Cronbach's Alpha, rho_A, and Composite Reliability, with a criterion of a value greater than 0.70 indicating good internal consistency. Finally, a collinearity test was conducted using the outer and inner Variance Inflation Factor (VIF) values, with a threshold of 5 or lower (Hair et al., 2021; Thakkar, 2020).

Once the measurement model has been determined to meet the criteria for validity and reliability, the next step is to conduct a goodness-of-fit test to assess the overall fit of the research model. In the PLS-SEM approach, goodness-of-fit evaluation can be performed by examining the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) values generated by the SmartPLS software (Hermita et al., 2023). The research model is considered to have a good level of fit if the SRMR value is below 0.08 and the NFI value is greater than 0.80 (acceptable) or 0.90 (better). These values indicate that the developed model adequately represents the relationships among constructs and is suitable for further analysis in testing research hypotheses (Hair et al., 2021; Hermita et al., 2023; Thakkar, 2020).

The final stage of data analysis is the evaluation of the structural model, which tests the causal relationships among the latent variables in the research model. Several tests are conducted in this stage. First, path coefficients are tested (hypothesis testing) to determine whether the strength of the relationship between variables is significant, as indicated by a p-value less than 0.05. Additionally, effect size (f^2) is used to measure the magnitude of each exogenous variable's influence on the endogenous variable, with values of 0.02 indicating a small effect, 0.15 a moderate effect, and 0.35 a large effect. Next, the model's predictive power was assessed using the coefficient of determination (R^2), which indicates the extent to which the independent variables explain the dependent variable in the research model, and was categorized as 0.75 (substantial), 0.50 (moderate), or 0.25 (weak). Finally, a structural model analysis was conducted using the predictive relevance test (Q^2) to assess the model's predictive ability; a Q^2 value greater than zero indicates good predictive relevance (Hair et al., 2021; Hermita et al., 2023; Thakkar, 2020).

RESULTS

Based on the descriptive statistics in Table 2 for all research indicators, the mean scores ranged from 2.703 (SD = 0.827) to 3.280 (SD = 0.791) on a 1–5 Likert scale, indicating that, in general, respondents rated the measured constructs at a moderate to somewhat positive level. The indicators with the highest mean scores were ICL2 (M = 3.280, SD = 0.791) and BI3 (M = 3.220, SD = 1.001), indicating that respondents were relatively more in agreement with the statements in those indicators. Furthermore, the skewness values ranged from -0.580 to 0.344, and the excess kurtosis values ranged from -0.566 to 0.248, showing a slight tendency toward the left (boundary -1) or the right (boundary +1) but still within acceptable limits (Kim, 2013; Tabachnick & Fidell, 2013). Thus, these results indicate that the data distribution is relatively symmetrical and falls into the mesokurtic category, i.e., it is normally distributed. Overall, skewness and kurtosis values within the ±1 range indicate that the data are normally distributed, thereby fulfilling the basic statistical assumptions for further analysis in the PLS-SEM framework.

EVALUATING THE MEASUREMENT MODEL

The measurement model was evaluated to ensure that the indicators validly and reliably measured the latent construct. First, validity analysis was conducted based on the outer loadings; the results showed that all indicators had loadings ranging from 0.835 to 0.940, all of which exceeded the minimum threshold of 0.7 (Hair et al., 2021). These values indicate that each indicator makes a strong contribution to reflecting the latent construct being measured. Next, an AVE analysis was conducted, showing that all constructs in the model had AVE values of ATU (0.752), BI (0.809), ECL (0.865), GCL (0.795), ICL (0.826), PEU (0.778), and PU (0.787), where all these values are greater than the threshold (≥ 0.50) (Hair et al., 2021). Based on these two test results, all constructs in this research model are deemed to have good convergent validity. Thus, the indicators used in each construct can adequately represent the latent variables being measured and are suitable for further analysis in the structural model. The detailed test results are presented in Table 2.

Table 2. Descriptive statistics and measurement model (outer VIF, validity, and reliability)

Item	M	SD	Excess kurtosis	Skew-ness	VIF	OL	EVA	CA	Rho_A	CR
Intrinsic Cognitive Load (ICL)										
ICL1	3.136	0.863	0.188	-0.107	3.424	0.910	0.826	0.930	0.930	0.950
ICL2	3.280	0.791	0.242	-0.234	3.752	0.920				
ICL3	3.144	0.751	-0.293	-0.124	3.202	0.905				
ICL4	3.161	0.833	0.248	-0.580	3.156	0.900				
Germane Cognitive Load (GCL)										
GCL1	2.847	0.809	-0.072	-0.198	2.844	0.888	0.795	0.914	0.915	0.939
GCL2	2.992	0.952	-0.255	-0.162	3.270	0.905				
GCL3	3.059	0.826	-0.083	0.344	2.718	0.879				
GCL4	2.907	0.92	-0.452	-0.076	3.089	0.894				
Extraneous Cognitive Load (ECL)										
ECL1	3.000	0.803	-0.179	0.100	2.860	0.910	0.865	0.922	0.923	0.950
ECL2	3.085	0.859	0.007	0.078	3.942	0.940				
ECL3	2.975	0.764	-0.373	-0.072	3.937	0.939				
Perceived Usefulness (PU)										
PU1	2.831	0.876	-0.437	0.034	2.792	0.887	0.787	0.910	0.910	0.937
PU2	2.703	0.827	-0.273	0.058	3.183	0.908				
PU3	2.822	0.899	-0.197	-0.207	2.549	0.877				
PU4	2.746	0.976	-0.366	0.311	2.556	0.877				
Perceived Ease of Use (PEU)										
PEU1	2.941	0.847	0.172	-0.14	2.253	0.848	0.778	0.905	0.908	0.933
PEU2	2.737	0.838	-0.013	0.094	3.230	0.906				
PEU3	3.178	0.85	-0.338	-0.100	2.447	0.874				
PEU4	2.924	0.976	-0.26	-0.012	3.028	0.898				
Attitude Toward Using (ATU)										
ATU1	2.822	0.83	-0.309	-0.104	2.478	0.874	0.752	0.890	0.892	0.924
ATU2	2.907	0.863	-0.198	0.023	2.064	0.835				
ATU3	3.153	0.755	-0.33	-0.144	2.387	0.874				
ATU4	3.186	0.843	-0.566	-0.024	2.647	0.885				
Behavioral Intention (BI)										
BI1	3.169	0.816	-0.008	-0.040	2.291	0.889	0.809	0.882	0.882	0.927
BI2	2.864	0.843	-0.258	0.006	2.562	0.904				
BI3	3.220	1.001	-0.56	-0.047	2.579	0.905				

Note: M = mean, SD = standard deviation, VIF = variance inflation factor, OL = outer loadings, AVE = average variance extracted, CR = composite reliability, CA = Cronbach's alpha.

Subsequently, a discriminant validity analysis was conducted using two approaches: the Fornell-Larcker criterion and the HTMT. The results of these analyses are presented in Table 3. First, the results of the Fornell-Larcker criterion show that the square root of the AVE for each construct is as follows: ATU (0.867), BI (0.899), ECL (0.930), GCL (0.892), ICL (0.909), PEU (0.882), and PU (0.887). These results indicate that the square root of the AVE for each construct is greater than its correlations with other constructs. Furthermore, the HTMT analysis indicates that all ratio values range from 0.179 to 0.883, which remain below the recommended threshold of 0.90 (Hair et al., 2021; Henseler et al., 2015). Based on these two testing results, it can be concluded that each construct exhibits greater variance within its indicators than across indicators of other constructs, thereby satisfying the discriminant validity criteria.

Table 3. Results of discriminant validity testing

Assessment using Fornell–Larcker criterion							
Construct	**ATU**	**BI**	**ECL**	**GCL**	**ICL**	**PEU**	**PU**
ATU	**0.867**						
BI	0.784	**0.899**					
ECL	0.405	0.298	**0.930**				
GCL	0.663	0.619	0.167	**0.892**			
ICL	0.532	0.473	0.166	0.776	**0.909**		
PEU	0.783	0.746	0.384	0.743	0.626	**0.882**	
PU	0.778	0.691	0.531	0.698	0.644	0.804	**0.887**
Assessment using Heterotrait–Monotrait ratio (HTMT)							
BI	0.883						
ECL	0.445	0.331					
GCL	0.734	0.689	0.181				
ICL	0.584	0.522	0.179	0.84			
PEU	0.871	0.833	0.418	0.814	0.680		
PU	0.862	0.772	0.580	0.765	0.699	0.883	

Second, a reliability analysis was conducted, yielding three test results: composite reliability, rho_A, and Cronbach's alpha; these results are presented in Table 2. The results of the construct reliability evaluation indicate that all variables in the model exhibit very high levels of reliability. Specifically, Cronbach's alpha values range from 0.882 to 0.930, rho_A values range from 0.882 to 0.930, and composite reliability values range from 0.924 to 0.950. All these values exceed the 0.70 threshold (Hair et al., 2021), indicating that each construct has high internal consistency and that the indicators used consistently measure the latent constructs in the developed research model. Cronbach's Alpha values are used to evaluate internal reliability based on correlations among indicators, whereas rho_A and Composite Reliability provide more accurate reliability estimates in the analysis (Hair et al., 2021). Thus, all constructs in this research model meet adequate reliability criteria.

Third, a collinearity analysis was conducted using VIFs, examining both outer VIFs (Table 2) and inner VIFs. Based on the outer VIF results, the VIF values for each indicator ranged from 2.064 to 3.942, all below the 5.00 threshold (Hair et al., 2021), indicating no significant collinearity among indicators within the same construct. Furthermore, the inner VIF results indicate the level of multicollinearity among constructs within the structural model, yielding the following values: ATU versus BI (1.000), ECL versus PEU (1.032), ECL versus PU (1.218), GCL versus PEU (2.520), GCL to PU

(3.548), ICL to PEU (2.520), ICL to PU (2.547), PEU to ATU (2.826), PEU to PU (2.668), and PU to ATU (2.826).

These results fall within the range of 1,000 to 3,548, which is also below the recommended threshold (5.00) (Hair et al., 2021). These results indicate that the relationships among the predictor variables in the structural model do not exhibit multicollinearity issues and do not interfere with the estimation of path coefficients in the PLS-SEM model. Thus, both the construct measurement indicators and the measurement variables used meet the criteria for the collinearity test.

Model Fit Analysis

Model fit analysis aims to evaluate the extent to which the constructed structural model represents the empirical data. In PLS-SEM analysis, several indices are commonly used; however, this study employed two indices, namely SRMR and NFI (Hermita et al., 2023). The SRMR value obtained was 0.057, which is below the threshold of 0.08 (Thakkar, 2020). The NFI value obtained was 0.836, indicating a fairly good level of model fit and is acceptable within the range of (0.80 to 0.90) in PLS-SEM analysis, as the primary focus of PLS-SEM is the model's predictive ability (Hair et al., 2021; Norabuena-Figueroa et al., 2025; Thakkar, 2020). Based on the SRMR and NFI values, this research model can be considered to have an adequate level of fit with the empirical data. This indicates that the difference between the observed correlation matrix and the model-predicted one is relatively small, and the model can be characterized as having a good fit.

Evaluating the Structural Model

The results of the structural equation model analysis are presented in Table 4 and Figure 4, which show that most of the hypothesized relationships among the constructs are statistically significant. The strongest relationship in the model was observed between ATU and BI ($\beta = 0.784$, $t = 19.606$, $p < 0.001$, $f^2 = 1.593$), indicating that attitudes toward the use of mobile robotics training kits play a substantial role in predicting behavioral intention. Another strong effect was found in the relationship between GCL and PEU ($\beta = 0.621$, $t = 7.700$, $p < 0.001$, $f^2 = 0.408$), indicating that relevant cognitive load significantly enhances users' perceived ease of use. Additionally, ECL on PU, PEU on ATU, and PEU on PU showed significant positive relationships ($p < 0.001$) with moderate to large effect sizes (f^2 ranging from 0.218 to 0.305), indicating that external cognitive load and perceived ease of use play a crucial role in shaping users' perceptions of usefulness and attitudes toward the use of the mobile robotics training kit.

Table 4. Structural model analysis

Predictor Construct	β	M	SD	T-Statistic	p-value	F²	Results
H1: ICL -> PU	0.173	0.174	0.07	2.469	0.014	0.048	Supported
H2: ICL -> PEU	0.101	0.101	0.083	1.205	0.229	0.011	Not Supported
H3: ECL -> PU	0.301	0.303	0.045	6.679	0.000	0.305	Supported
H4: ECL -> PEU	0.264	0.267	0.05	5.262	0.000	0.180	Supported
H5: GCL -> PU	0.185	0.184	0.091	2.034	0.042	0.040	Supported
H6: GCL -> PEU	0.621	0.617	0.081	7.700	0.000	0.408	Supported
H7: PU -> ATU	0.419	0.418	0.084	4.972	0.000	0.191	Supported
H8: PEU -> ATU	0.447	0.447	0.081	5.492	0.000	0.218	Supported
H9: PEU -> PU	0.442	0.44	0.08	5.513	0.000	0.301	Supported
H10: ATU -> BI	0.784	0.782	0.04	19.606	0.000	1.593	Supported

Note: β = path coefficient, M = sample mean, SD = standard deviation, F^2 = effect size.

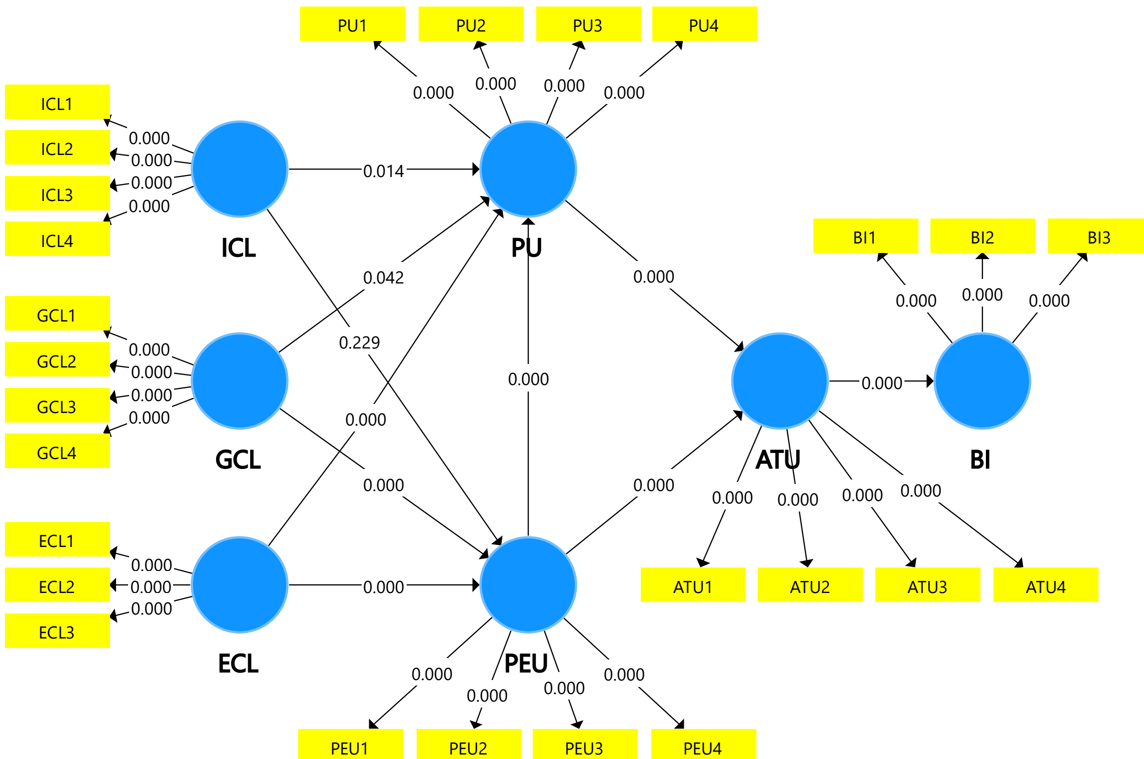

Figure 4. Evaluation of the structural model of the mobile robotics training kit

Furthermore, the relationships between ECL and PEU and between PU and ATU were also statistically significant ($p < 0.001$). They had moderate effect sizes, highlighting the contribution of these constructs to the model's overall explanatory power. Meanwhile, ICL on PU and GCL on PU showed significant positive effects at the 5% level of significance ($p < 0.05$). However, the effect sizes were relatively small, indicating a limited yet meaningful contribution to perceived usefulness. Among the ten hypotheses tested, nine were supported. In contrast, one hypothesis was not supported, namely the relationship between ICL and PEU ($\beta = 0.101$, $t = 1.205$, $p = 0.229$, $f^2 = 0.011$), indicating that intrinsic cognitive load does not significantly influence perceived ease of use in this context. The significance of structural relationships was determined based on a p-value criterion of < 0.05, indicating a statistically significant effect at the 5% significance level (Hair et al., 2021; Tabachnick & Fidell, 2013).

Next, an analysis of the coefficient of determination (R^2) was conducted, with the results presented in Table 5. The R^2 results indicate the model's ability to explain the variance in the endogenous construct in this study (Hair et al., 2017; Thakkar, 2020). First, the PU construct has an R^2 value of 0.756, indicating that 75.6% of the variance in PU can be explained by the predictor variables in the model, with a small ICL effect ($f^2 = 0.048$), small GCL ($f^2 = 0.040$), moderate ECL ($f^2 = 0.305$), and moderate PEU ($f^2 = 0.301$). Second, the PEU construct has an R^2 value of 0.625, indicating that 62.5% of the PEU variance can be explained by the predictor variables in the model, with impact categories showing no effect for ICL ($f^2 = 0.011$), a large effect for GCL ($f^2 = 0.408$), and a moderate effect for ECL ($f^2 = 0.180$). Third, the ATU construct has an R^2 value of 0.676, meaning that 67.6% of the variance in ATU can be explained by variables with the impact categories of moderate PU ($f^2 = 0.191$) and moderate PEU ($f^2 = 0.218$) as the primary predictors. Finally, the BI construct has an R^2 of 0.614, indicating that the ATU explains 61.4% of the BI variance, with the high impact criterion ($f^2 = 1.593$). Additionally, the adjusted R^2 values, which are relatively close to the R^2 values across all constructs, indicate that the model has good estimation stability and does not exhibit bias due to the number of predictors. Overall, the R^2 values for all constructs fall in the moderate to substantial range, indicating that the model has strong explanatory power for the endogenous variables in this study.

Table 5. Testing of the coefficient of determination and predictive relevance

Variable	Determinant coefficient (R^2)		Predictive relevance (Q^2)		
	R Square	R square adjusted	SSO	SSE	Q^2 (=1-SSE/SSO)
ATU	0.676	0.67	472	200.575	0.575
BI	0.614	0.611	354	147.992	0.582
PEU	0.625	0.615	472	180.771	0.617
PU	0.756	0.747	472	174.721	0.630
ECL	-	-	354	112.933	0.681
GCL	-	-	472	169.400	0.641
ICL	-	-	472	146.851	0.689

Furthermore, an R^2 value of 0.614 indicates that the research model explains 61.4% of the variance in students’ BI regarding the use of the mobile robotic training kit. Although 38.6% of the variance is still explained by factors outside the model, such as individual characteristics, social support, prior technology experience, or facilitation conditions, the proportion of variance successfully explained indicates that cognitive and perceptual factors are the primary determinants in shaping students’ behavioral intentions (Bloodworth et al., 2023; Pekarcikova et al., 2025; Phokoye et al., 2024; Selcuk et al., 2024). From these results, GCL is the most dominant factor influencing PEU, while ECL consistently influences PU and PEU. Conversely, ICL makes only a limited contribution to PU and has no significant influence on PEU. This pattern indicates that students’ intention to use the mobile robotic training kit is shaped more by the quality of the learning experience generated by the technology than by the inherent complexity of the robotics material itself. In other words, students do not evaluate the technology based on how difficult the material being studied is, but rather on the extent to which it reduces irrelevant cognitive load and facilitates meaningful cognitive engagement.

Finally, a predictive relevance analysis (Q^2) was conducted, and the results are shown in Table 5. Based on the analysis results, all constructs have positive Q^2 values: ATU (0.575), BI (0.582), ECL (0.681), GCL (0.641), ICL (0.689), PEU (0.617), and PU (0.630); thus, all exhibit strong predictive relevance. A Q^2 value > 0 indicates that the model has strong predictive relevance, as it can accurately reconstruct the observed values of the indicators (Hair et al., 2017; Thakkar, 2020). Among the constructs analyzed, ICL (Q^2 = 0.689) and ECL (Q^2 = 0.681) exhibit the highest predictive relevance values, indicating that these two constructs have an excellent ability to explain the variance of their respective indicators. Meanwhile, the ATU (0.575) and BI (0.582) constructs also showed fairly high Q^2 values, confirming that the model has adequate predictive power regarding attitude and behavioral intention variables.

DISCUSSION

THE CONTRIBUTION OF COGNITIVE LOAD TO THE ACCEPTANCE OF A MOBILE ROBOTICS TRAINING KIT

The main finding of this study lies in the empirical evidence that students’ cognitive experiences while using the training kit serve as a crucial foundation for the development of technology acceptance. Previous research on the assessment of robotic technology acceptance in the learning process has focused on psychological factors (X. Chen et al., 2025; Lei et al., 2022), pedagogical factors

(N. Ali et al., 2023), and the characteristics of the technology used (S. Chen et al., 2023; Di Battista et al., 2023); however, the cognitive processes of users when utilizing robotic technology in the learning process have not yet been explored in depth. The results of this study indicate that robotics education involves the integration of hardware such as sensors, microcontrollers, and actuators, as well as programming algorithms and technical problem-solving (Chookaew et al., 2021; Setyawan, Sukardi, Risfendra, Tri Putra Yanto, & Tze Kiong, 2025). Given the complexity of this learning process, cognitive load is not merely an additional factor but a fundamental condition that shapes students' perceptions of whether technology is useful and easy to use in the learning process. Thus, this study expands the understanding of TAM by positioning cognitive processes as a key antecedent in the formation of technology acceptance perceptions.

First, the research results show that ICL has a significant effect on PU ($\beta = 0.173$; $p = 0.014$), but ICL does not have a significant effect on PEU ($\beta = 0.101$; $p = 0.229$). This finding is highly significant because it indicates that the complexity of robotics learning materials is not always perceived as a barrier by students when using the training kit; rather, the training kit is considered beneficial for students in facilitating robotics learning. These results align with CLT, which indicates that learning that demands authentic problem-solving (such as using a training kit in mobile robot applications) shows that high intrinsic load is not always negative; rather, it can signify cognitive engagement relevant to achieving established learning objectives (Sweller, 2023, 2024). In the use of technology, perceived usefulness often increases when technology helps users manage complex and meaningful tasks, rather than when it is simply easy to use (Davis, 1989). These findings are further supported by previous research indicating that the robotics learning process typically involves high cognitive demands related to procedural reasoning, problem-solving, and concept integration; consequently, the benefits of the learning training kit become increasingly evident when students use it to bridge the complexity of such learning (Bloodworth et al., 2023; Chu et al., 2022).

Although ICL showed no significant correlation with PEU, these findings are nonetheless noteworthy. They indicate that students can distinguish between the complexity of the learning materials and the ease of use of the training kit. This is influenced not only by the use of the training kit but also by the instructional design, which makes complex learning content easier for students to understand. This approach begins with foundational learning to reinforce concepts and skills, followed by project planning, implementation, and evaluation. This process functions as instructional scaffolding, helping students progressively adapt to task demands and reducing students' cognitive load during learning (Koć-Januchta et al., 2022; Skulmowski & Xu, 2022). Furthermore, the perception of ease of use in learning technology is likely more sensitive to usability quality and interaction design than to the inherent complexity of the content; thus, intrinsic cognitive load is not always a strong predictor of perceived ease of use when the technology is designed to be sufficiently intuitive and aligned with the learning progression (Janson & Ernst, 2024; Kemp et al., 2024). Thus, these findings refine the assumption in the literature that high intrinsic cognitive load always reduces perceived ease of use; in the context of well-structured learning, students can still view the technology as manageable even when the material being studied is highly conceptual.

In addition, students' internal factors, such as motivation and prior learning experiences, also influence their ICL. First, students with high learning motivation tend to view cognitive challenges as a natural part of the competency acquisition process, so that greater mental effort does not become a barrier to technology use (W. Li et al., 2024; Wu et al., 2022). Furthermore, students' intrinsic motivation and engagement in learning play a crucial role in fostering positive perceptions of the use of learning technology, even when assigned tasks are highly complex. Second, prior experience with learning technology enables students to develop more mature knowledge schemas, allowing them to manage the complexity of the material more efficiently (Barz et al., 2024). Students with prior relevant experience tend to have more organized cognitive schemas, enabling them to integrate new information with existing knowledge. Consequently, the cognitive demands arising from using the mobile robotic training kit are not perceived as difficulties with operating the technology but rather as a natural part of completing complex learning tasks. Thus, the non-significant relationship between ICL and PEU in this study indicates that perceptions of ease of use are also shaped by user characteristics beyond the complexity of the learning material (X. Chen et al., 2025; de Oliveira Santini et al., 2025). This finding extends the integration between CLT and TAM by showing that the impact of intrinsic cognitive load on technology acceptance can be mitigated by personal factors, such as motivation and prior experience, enabling students to continue viewing the technology as easy to use even as they engage in cognitively challenging robotics learning activities.

Second, this study found that ECL has a significant effect on PU ($\beta = 0.301$; $p < 0.001$) and PEU ($\beta = 0.264$; $p < 0.001$). These results reveal that students' perceptions of the benefits and ease of use of the mobile robotic training kit are strongly influenced by the quality of the instructional design and the presentation of information during the learning process. With an intuitive interface design, structured content, and a systematic sequence of activities, students can allocate more cognitive resources toward understanding robotics concepts and completing learning tasks rather than overcoming operational obstacles (Anđić et al., 2024; Huang et al., 2025). Reducing irrelevant cognitive load not only makes the technology easier to use but also enhances students' confidence that the technology genuinely helps them achieve their learning objectives. In other words, students perceive that the training kit they use can help them understand concepts, improve learning efficiency, and complete robotics tasks (S. Li et al., 2024). Thus, it can be concluded that ECL is a component that can be controlled through appropriate instructional design. The success of implementing robotics technology in vocational education is determined not only by the sophistication of the technology's features but also by the instructional design's ability to minimize irrelevant cognitive load, thereby allowing students to focus their attention on the process of knowledge construction and the development of meaningful skills (Alam & Mohanty, 2024; Phokoye et al., 2024).

Third, the results indicate that GCL has a significant effect on PU ($\beta = 0.185$; $p = 0.042$) and a very strong effect on PEU ($\beta = 0.621$; $p < 0.001$). These results reveal that the greater the relevant cognitive effort students allocate to constructing, integrating, and automating knowledge during the use of the training kit, the more positive their perceptions of the technology become. Unlike ICL and ECL, which should be minimized, GCL is facilitated through learning activities that encourage reflection, exploration, problem-solving, and the application of concepts in authentic contexts (Ackermann et al., 2025; Anđić et al., 2024). The positive influence of GCL on PU and PEU indicates that students perceive the training kit as more beneficial when it fosters meaningful cognitive engagement and helps them build a deeper understanding of robotics concepts (Huang et al., 2025). In vocational education, the perception of benefits stems not only from completing practical tasks but also from the belief that the learning experiences gained contribute to the development of competencies relevant to the needs of the industrial world (Chookaew et al., 2021). Thus, GCL serves as a mechanism linking meaningful learning activities with positive evaluations of the instructional value of technology.

The Contribution of the Traditional TAM Theoretical Framework to the Acceptance of a Mobile Robotics Training Kit

The relationships among the TAM constructs in this study provide strong empirical support for the internal model of technology acceptance. First, the results show that PEU has a significant effect on PU ($\beta = 0.442$; $p < 0.001$). This finding reveals that when students perceive the training kit as easy to use, they will more readily recognize its benefits for learning, as this serves as a cognitive prerequisite that allows users to shift their attention from operational issues toward an understanding of the technology's functional value (Davis, 1993; Pekarcikova et al., 2025). In the robotics learning process, students are not burdened by complex procedures; the mobile robotic training kit features an intuitive interface and a systematic workflow. Consequently, learning focuses on exploring the training kit to help understand concepts, complete tasks, and support learning performance. These results support previous research indicating that the relationship between PEU and PU is one of the most stable pathways within the TAM, particularly in the evaluation of educational technology (I. Ali & Warraich, 2025; Marikyan et al., 2026). Furthermore, PU in learning technology arises from a smooth, understandable user experience, so that its usefulness often only becomes apparent after users feel the technology is easy to access, learn, and control (Song et al., 2023).

The results of the study also show that PU ($\beta = 0.419$; $p < 0.001$) and PEU ($\beta = 0.447$; $p < 0.001$) both have a significant effect on ATU. These results reveal that students' attitudes toward the use of training kits are shaped by two main factors: the extent to which the technology is beneficial for learning and the extent to which it can be used without excessive errors. Within the TAM framework, the PU construct reflects the rational value that technology can enhance student performance or learning outcomes. Meanwhile, the PEU construct represents the low level of operational barriers, making interaction with the technology feel smoother and less mentally taxing. The combination of these two constructs results in a more positive evaluation of the technology used by students (N. Ali et al., 2023; Davis, 1993). Furthermore, from an expectancy-value perspective, students will exhibit a more positive attitude when they assess that the effort required to learn and use technology is comparable to, or even less than, the learning benefits gained (Hebibi et al., 2025). Thus, ATU is pragmatic and experiential because positive attitudes emerge when technology successfully delivers tangible learning benefits through a smooth, understandable, and student-learning-supportive usage process (X. Chen et al., 2025; Liu et al., 2025).

The strongest influence within the TAM theoretical framework was found in the path from ATU to BI ($\beta = 0.784$; $p < 0.001$; $f^2 = 1.593$). These results reveal that students' intention to continue using the mobile robotic training kit is strongly determined by their overall affective and cognitive evaluations of the technology. This finding reinforces that in vocational school learning, the attitude construct serves as the primary psychological mechanism that translates perceptions of benefits and ease of use into behavioral commitment to continue using the technology (Marikyan et al., 2026; Yakubu et al., 2025). Students' positive attitudes are formed when they directly experience that the technology used supports task success, reduces practical barriers, and provides a satisfying learning experience. Thus, once a positive attitude has been formed, users' intentions tend to strengthen significantly (Barz et al., 2024). These findings are also supported by previous research indicating that attitude serves as a very strong link between user perceptions and technology adoption intentions, particularly in the adoption of educational technology that demands active engagement and positive user experiences (Marikyan et al., 2026; Yang et al., 2025). Therefore, strategies to enhance the sustainability of training kit usage should not stop at providing functional technology but should be directed toward creating meaningful, seamless learning experiences that foster an emotional conviction that the technology is indeed worth continuing to use.

Overall, the results of this study indicate that students' acceptance of the mobile robotic training kit is shaped through a multi-layered mechanism. In the initial stage, students face various forms of cognitive load when interacting with robotics tasks. In the next stage, these cognitive experiences shape their perceptions of the training kit's ease of use and usefulness. In the final stage, these two perceptions shape attitudes that, in turn, drive behavioral intentions to continue using the technology. These results reveal that adopting educational technology is a multidimensional process in which learning experiences, usability, and perceptions of pedagogical value influence one another simultaneously (X. Chen et al., 2025). In vocational education, these findings are particularly substantial because students are not passive users but rather performers of authentic, complex, and problem-solving-oriented technical tasks. Consequently, technology is accepted not merely when it functions well, but when it helps students think, act, and complete tasks more effectively (Ariansyah et al., 2024; Souza et al., 2021). These results also indicate that the acceptance of technology in vocational education should not be reduced to the question of "whether this tool is advanced or easy to use," but rather understood as the success of the learning ecosystem in transforming the complexity of tasks into manageable, meaningful, and worthwhile learning experiences for students (Candido & Cattaneo, 2025; L. Hsu, 2024; Liu et al., 2025).

PRACTICAL AND THEORETICAL IMPLICATIONS OF THE STUDY

The findings of this study have practical and theoretical implications for the implementation of mobile robotic training kits in vocational education. From a practical perspective, teachers need to implement robotics education in a step-by-step manner, focusing on mastery of basic concepts, guided practice, and independent projects. This approach allows students to focus their cognitive resources on developing conceptual understanding and problem-solving skills, rather than on technical difficulties that are irrelevant to the learning objectives. Mobile robotic training kits can be used to facilitate progressive learning, ranging from basic robotics concepts to more authentic applications, such as line-following, wall-following, and smartphone-controlled robots, thereby supporting the connection between theory and practice. Furthermore, research indicates that using training kits with clear interfaces, structured materials, and systematic learning activities can reduce extraneous cognitive load, thereby enhancing the efficiency of information processing and the quality of students' learning experiences. From a broader perspective, schools and educational media developers need to ensure that the design and implementation of training tools can create a positive, structured initial learning experience that supports students' success in mastering robotics competencies from the early stages of learning.

Second, this study makes a theoretical contribution by expanding TAM's explanatory power by integrating CLT to explain acceptance of mobile robotic training kits in vocational education. Unlike conventional TAM research, which generally treats perceived usefulness and ease of use as the main predictors of technology usage intention, this study's results indicate that these perceptions are shaped by cognitive mechanisms through ICL, ECL, and GCL. This study reveals that GCL and ECL have a greater contribution to technology acceptance than ICL. Thus, in complex learning environments, technology acceptance is not solely determined by the difficulty level of the material being studied, but by the extent to which technology can facilitate the knowledge construction process and reduce irrelevant cognitive barriers. This study expands the role of CLT from a previously dominant theory of learning effectiveness to a conceptual framework capable of explaining the mechanisms underlying the formation of educational technology acceptance. Even more interestingly, the model's ability to explain 61.4% of the variance in students' behavioral intentions indicates that integrating CLT and TAM provides a strong theoretical foundation for understanding the relationships among cognitive processes, instructional design, and technology acceptance in vocational education.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study has several limitations that should be considered when interpreting the findings and designing future research, despite the results indicating a positive impact. First, this study used a relatively small sample of 118 students, specifically from a vocational high school program specializing in industrial electronics. Therefore, any generalization regarding the use of mobile robotics training devices in other vocational education programs with similar learning processes should be made with caution. Second, all constructs in this study were measured via self-report, leaving open the possibility of common-method bias and discrepancies between students' perceptions and their actual usage behavior. Third, although the model demonstrated clear effects, with 9 out of 10 hypotheses supported, the relationship between intrinsic cognitive load and PEU was not significant. This result indicates that there are still other factors outside the model, such as prior knowledge, teacher quality, previous experience with robotics, and the design characteristics of the training kit's interface and tasks, that have not been fully accounted for in this study.

Given the limitations of this study, the researcher offers several recommendations for future research. First, this model needs to be tested on a larger and more diverse sample with similar learning characteristics, such as robotics, microcontrollers, or embedded systems, at the vocational high school level. Second, the model should be expanded to include other pedagogical, individual, and technological variables to gain a more comprehensive understanding of the assessment of the acceptance of mobile robotic training kits in vocational education.

CONCLUSIONS

Based on the results of the measurement and structural equation model analyses, this study concludes that the mobile robotic training kit is a robotics learning technology that vocational education students accept positively. This acceptance is strongly explained by an extension of the TAM model integrated with CLT theory. Empirically, the developed model demonstrates good validity and reliability, as well as an adequate model fit. Thus, the developed model is valid for explaining the acceptance of the mobile robotic training kit in robotics education. The main findings indicate that extraneous and germane cognitive load play significant roles in shaping PEU and PU. Meanwhile, intrinsic cognitive load significantly influences PU but not PEU. These results confirm that in robotics education, technology acceptance is not only determined by functional perceptions of ease of use and utility but is also strongly influenced by how the technology manages students' cognitive demands during the learning process. Thus, the better a training kit is designed to reduce irrelevant cognitive load while simultaneously fostering productive cognitive engagement, the greater the likelihood that students will perceive the technology as easy to use and beneficial for their learning.

Furthermore, this study confirms that the core constructs of the TAM remain consistent in explaining the adoption of robotics learning technology in vocational education, where PEU has a significant influence on PU, and together they form the ATU, which in turn serves as the strongest predictor of BI. The findings of this study indicate that technology acceptance in robotics education is determined more by the quality of the cognitive experience facilitated by the technology than by the material's complexity. These results confirm that reducing irrelevant cognitive load and enhancing meaningful cognitive engagement are essential prerequisites for fostering sustainable acceptance of learning technologies. By integrating CLT and TAM, this study offers a new perspective that the successful adoption of educational technology in complex learning environments is fundamentally both a cognitive and a pedagogical phenomenon.

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APPENDIX: RESEARCH INSTRUMENT

Assessment variables	Assessment items	
Intrinsic Cognitive Load (ICL)	ICL1	The tasks involved in this learning process are highly complex.
	ICL2	I need to understand multiple concepts simultaneously in order to complete the assigned tasks.
	ICL3	I must exert considerable cognitive effort to understand the relationships among the components of the microcontroller system.
	ICL4	Numerous elements must be considered simultaneously when using this training kit.
Germane Cognitive Load (GCL)	GCL1	I strive to understand the concepts comprehensively, rather than merely focusing on the technical procedures.
	GCL2	I attempt to relate the new material to my prior knowledge.
	GCL3	The tasks in this learning process help me develop a deeper understanding.
	GCL4	I focus on genuinely understanding how this microcontroller system operates.
Extraneous Cognitive Load (ECL)	ECL1	I find it difficult to identify important information when completing the tasks.
	ECL2	The presentation of the learning materials requires me to exert more effort than necessary.
	ECL3	The layout or usage instructions of the training kit do not sufficiently support my understanding.
Perceived Usefulness (PU)	PU1	The use of the mobile robotic training kit helps me understand the learning materials more effectively.
	PU2	This training kit enhances my learning productivity.
	PU3	The mobile robotic training kit improves the quality of my practical work outcomes.
	PU4	Overall, this training kit is beneficial to my learning process.
Perceived Ease of Use (PEU)	PEU1	My interaction with the mobile robotic training kit is clear and understandable.
	PEU2	I find the training kit easy to operate.
	PEU3	I can quickly learn how to use this training kit.
	PEU4	Overall, the mobile robotic training kit is easy to use.
Attitude Toward Using (AT)	ATU1	Using the mobile robotic training kit in the learning process is a good idea.
	ATU2	I enjoy using this training kit during the practical learning activities.
	ATU3	I have a positive attitude toward the use of this training kit.
	ATU4	The use of this training kit makes the learning process more engaging.
Behavioral Intention (BI)	BI1	I am willing to use the mobile robotic training kit in practical learning activities.
	BI2	I intend to use the mobile robotic training kit regularly in the learning process.
	BI3	I expect to continue using the mobile robotic training kit in the future.

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