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The exploration of continuous learning intention in STEAM education through attitude, motivation, and cognitive load

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Abstract

Background: This study proposes a learning cycle and a comprehensive research framework that integrates Bloom's taxonomy: the cognitive domain (cognitive load), affective domain (attitude and motivation) and psychomotor domain (implementation of science, technology, engineering, arts, and math [STEAM] activities) to explore the relationship between these learning domains and learning intention. The proposed innovative mediated-moderation model includes second-order factors derived from the technology acceptance model (TAM) (perceived usefulness, perceived ease of use, and perceived enjoyment), the attention, relevance, confidence and satisfaction (ARCS) model, and cognitive load (mental load and mental effort) to explain the continuous learning intention of STEAM education.

Results: A teaching material was designed for the STEAM activity, and an empirical experiment was subsequently conducted. The empirical experiment of STEAM activities with our design teaching material (micro:bit with artificial intelligence-based concept) was conducted at a university and an elementary school; a total of 145 questionnaire survey data were collected after the activities. University student participants were 20–24 years old and the elementary school student participants were at the K5–K6 level. The results showed that perceived usability directly influenced learning intention and strengthened the relationship between learning attitudes and intention. The ARCS plays a critical moderating role that positively influenced perceived usability and strengthened its effects on learning attitudes. Regarding the mediating effects, cognitive load negatively influenced perceived usability.

Conclusions: The findings of this study revealed that critical factors affect students' learning attitudes and intentions regarding STEAM education. The theoretical and educational implications of these findings were proposed to future instructors.

Highlights

- The STEAM learning cycle was proposed to describe four phases for successful STEAM learning.
- Affect factors of learning intention in STEAM education were investigated.
- Motivation factors positively influences perceived usability and learning attitude.
- Cognitive load has a significant negative effects influences perceived usability.
- Perceived usability directly influences learning intention and strengthens the relationship between attitudes and intention.

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Keywords: STEAM education, Technology acceptance model, Cognitive load, ARCS motivation model, STEAM learning cycle, Artificial intelligence, Learning performance

Introduction

Recently, the concepts of STEAM (science, technology, engineering, arts, and math) have been examined to determine the benefits of enhancing the cognitive domain of learning of memory, reaction time, and innate intelligence (Pabalan et al., 2018); psychomotor domain of physical measure, coordination, and skill (Ariyanto et al., 2019); and affective domain of self-confidence, self-motivation, collaboration, personal grooming, and time administration (Ramma et al., 2018). In cognitive domain studies, several previous studies examined the effects of STEAM in enhancing creative thinking (Bassachs et al., 2020; Land, 2013), career decision-making (Abe & Chikoko, 2020), cognitive structures for engineering design thinking (Lin, Chai, et al., 2021; Lin, Wu, et al., 2021), and cognitive appraisals and boredom (Ekatushabe et al., 2021). The psychomotor domain refers to skills parallel with physical growth and development to implement a specific task (Gülen et al., 2019). In the psychomotor domain, the relationship between STEAM education and learning performances, such as excitement, manual control, skill, fitting situations, and creating improvement, has been examined in previous studies (Bassachs et al., 2020; Marín-Marín et al., 2021). In the affective domain, several previous studies adopted the technology acceptance model (TAM) to explain the attitude toward continuous learning intention (Haji et al., 2017; Huang & Liu, 2021; Wu & Chen, 2017), and motivations for STEAM education (Conradty & Bogner, 2020). Thus, considering technology usage in enhancing self-directed learning (Curran et al., 2019), learning motivation (Dunn et al., 2019), and skill improvement (Radhamani et al., 2021), more theoretical and empirical research is essential to discover the influence of the ARCS (attention, relevance, confidence, and satisfaction) motivation model (Keller, 2009). Technology usage in STEAM education also has the benefits of decreasing cognitive load (mental load and mental effort) and improving students' learning intentions (Cheng, 2017; Costley & Lange, 2017).

In addition, previous educational studies have provided evidence of the benefits of STEAM education in student learning (Gao et al., 2020), design thinking (Lin, Chai, et al., 2021; Lin, Wu, et al., 2021), and professional development (Shernoff et al., 2017). However, artificial intelligence (AI) application and needs represent the increasing trend of education because it advances the learners' capabilities of learning analytics, which may increase their workplace competitiveness (Zawacki-Richter et al., 2019). However, the integration of the above TAM concepts and AI application functions in the education process has not been well examined (Gülhan & Şahin, 2018).

Bloom (1956) proposed a taxonomy of learning domains that identified three domains of educational activities: the cognitive, affective, and psychomotor domains. Recently, Bloom's taxonomy concepts have been widely used in many education studies, such as those applied in science and technology courses, measuring learning outcomes (Zorluoglu et al., 2019), social studies curriculum (Koc et al., 2020), and estimating the objects in information technology and software course curricula (Ocak et al., 2020). In other words, Bloom's taxonomy is a useful guide to help educators develop curricula. The three critical attributes are as follows: first, the cognitive domain focuses on mental skills that involve the knowledge and development of intellectual skills (Bloom, 1956). The affective domain concerns growth in feelings or emotional status, such as attitude or motivation (Krathwohl et al., 1973). The psychomotor domain is related to physical skills (Simpson, 1972). Accordingly, based on Bloom's taxonomy (1956), the learner learns new knowledge (cognitive domain), attitudes (affective domain), and skills (psychomotor) in a learning activity.

This paper proposes a STEAM learning cycle that reveals four phases (cognitive, psychomotor, and affective domains, and continuous learning intention) for successful STEAM learning.

In the first phase, a learner starts to learn knowledge (cognitive domain), and the high/low level of cognitive load will affect the learner's outcome of implementation of steam activity in the next psychomotor domain phase (Fig. 1). First, from the cognitive domain viewpoint, cognitive development can be seen as the resource allocation of the knowledge development process (Lu et al., 2020; Yafie et al., 2020). In the second phase (psychomotor domain), a heavy cognitive load may negatively affect learning performance because individuals cannot handle the complexity and the infinity of the abundant information at once as an input (Kozlovskiy et al., 2021). In the third phase (affective domain), the successful implementation experience of STEAM activity in the second phase would increase the positive attitude and enhance the motivation towards continuous learning intention in the fourth phase. Continuous learning intention refers to the learners' willingness to engage or attend STEAM activity in the future. The definition of continuance intention is derived from a previous study (Dai et al., 2020)

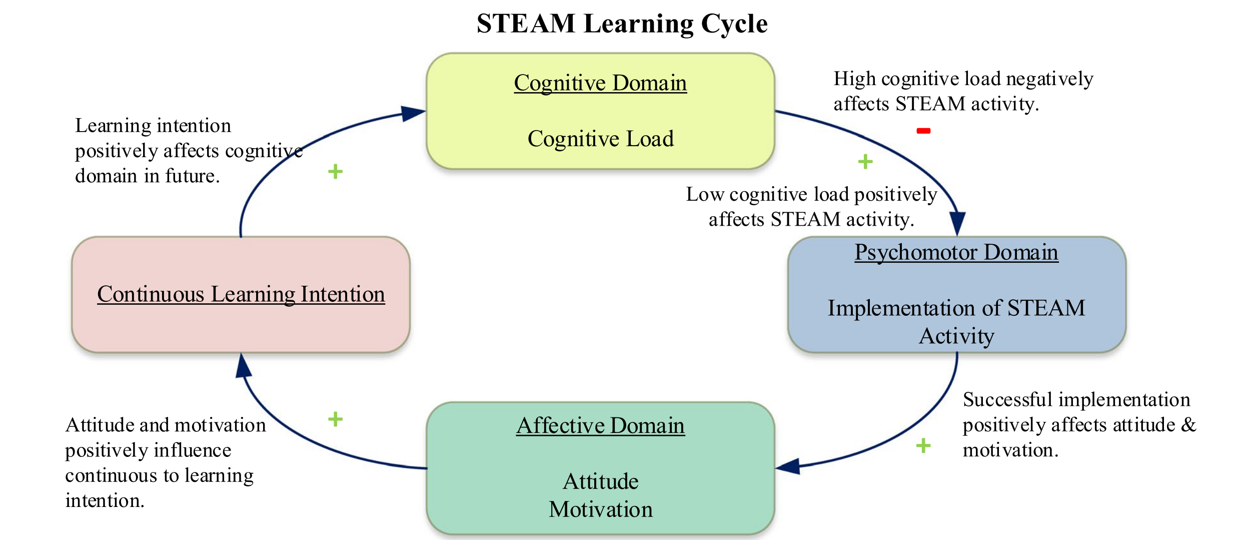

Fig. 1 STEAM learning cycle

that denotes the intention of students to continue learning STEAM after the teaching activity. The same idea has been adopted in learning intention assessment of AI-enabled application (Fu et al., 2020) and MOOC (Dai et al., 2020). In the fourth phase, a high level of STEAM continuous learning intention motivates the learner to start the next phase in the STEAM learning cycle. The successful implementation of STEAM activity positively triggers the learners' affective domains, such as attitude and motivation toward continuous learning intention in the future.

Previous STEAM studies focus on the relationship between Bloom's cognitive domain (such as six layers of cognitive domain) and learning performance. Most STEAM studies have focused on developing engineering design thinking, teachers' perceptions (Margot and Kettler 2019), and the cognitive domain applied in learning performance (Fletcher, 2018; Gao et al., 2020). However, few studies have integrated affective factors in the affective domain and examined how to apply them in STEAM education. Affective domain assessment for STEAM is one of the most important assessments for STEM education (Gao et al., 2020). A previous study investigated attitudes, beliefs, motivation, and interest towards the intention of disciplines in STEM. The well-designed STEM activity not only increased students' knowledge bust, but also their affective intention for STEM (Apedoe et al., 2008).

The STEAM learning activity's emphasis on learning-by-doing usually requires learners to finish a specific task that takes a longer time to assimilate new things learned and apply them to daily life practices (Gao et al., 2020; Wahono et al., 2020). Therefore, affective factors such as attitude or motivation for enhancing learners' patience to successfully complete learning tasks need to be clarified. In the psychomotor domain, learning objectives focus on behavioral changes and skill development. Skills denote the ability to physically manipulate or instruments to complete a specific task. We believe that the assessment of the psychomotor domain, such as implementing STEAM activity, also plays a critical role in continuous learning intention in STEAM education. Thus, this study proposes a comprehensive research framework that integrates Bloom's (1956) taxonomy: cognitive domain (cognitive load), affective domain (attitude and motivation), and psychomotor domain (implementation of STEAM activity) to explore the relationship between these learning domains and learning intention. We adopted cognitive load factors from cognitive load theory to the cognitive domain, attitude factors (perceived attitude and learning intention) from TAM and motivation factors from Keller's (1983) ARCS theory to the affective domain, and implemented micro:bit with AI learning activity for skill training assessment in the psychomotor domain to develop a comprehensive assessment framework for STEAM learning intention. The research framework is illustrated in Fig. 2. Micro:bit is an embedded system based on the Advanced RISC Machine (ARM) architecture, designed by the British Broadcasting Corporation (BBC) for use in computer education in the UK (https://en.wikipedia.org/wiki/Micro_Bit).

Previous studies have considered the factors of active online interaction and collaboration to improve students' learning performance in STEM education (Barrett et al., 2020; Granić & Marangunić, 2019; Huang & Liu, 2021).

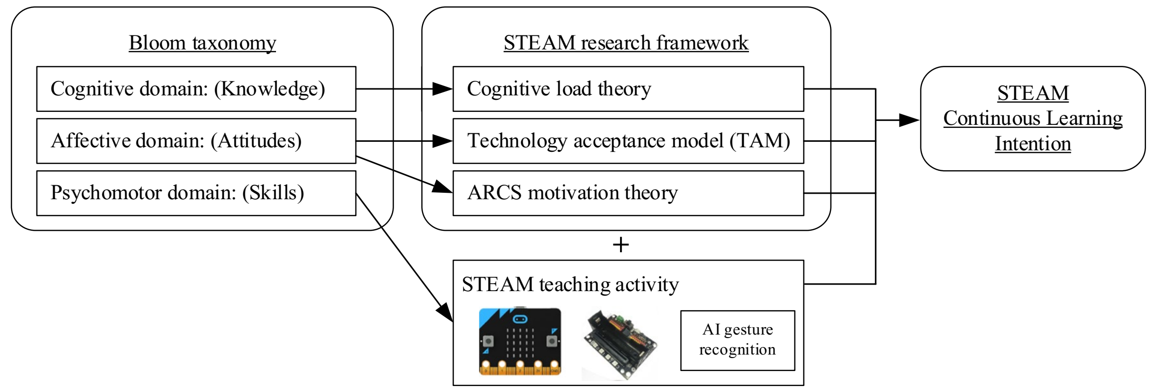

Fig. 2 Research framework

However, several gaps in the existing literature need to be addressed. First, the critical factors influencing students' learning intentions and attitudes toward STEAM education are unclear. Second, only a few education studies have examined the multi-perspectives that include cognitive, affective, and psychomotor domains affecting the attitude and learning intention toward STEAM education. With the increasing attention in STEAM education development and application, these unsolved issues have become critically important and need to be addressed further. Therefore, this study introduces a new theoretical model (Fig. 2) that integrates the above-mentioned multi-learning domains to explain how and why these factors affect STEAM learners' learning intention in order to address these research gaps. Therefore, this study aims to explore the latent factors that can enhance STEAM continuous learning intention. These not only contribute to the research on learning motivation factors of learners, but also improve the application of TAM, cognitive load theory, and ARCS theory in STEAM education. Furthermore, the moderation effect analysis allows this study to provide new insights for STEAM educators in evaluating and improving teaching activities.

Theoretical background and hypothesis development

Technology acceptance model (TAM)

The TAM theory was proposed to explore the behavior of user acceptance of information service systems based on the social psychology perspective (Mu & Jong, 2018; Zhang et al., 2019). Davis's TAM proposes that perceived usefulness effects significantly influence users' attitudes and behavioral intentions (Davis, 1989). The TAM theory, one of the most popular and important theoretical models regarding technology acceptance, provides a fundamental background for understanding individuals' perception of specific technology acceptance behavior of intention, such as massive open online courses' (MOOCs) continuance intention (Wu & Chen, 2017). Considering the adoption of TAM in Web 2.0 and technologies in education, students' and teachers' perceived usefulness of the technologies had a positive impact on their attitudes toward the intention of using Web 2.0. However, contrary to the original TAM, in a later TAM, perceived ease of use had no significant influence on perceived usefulness (Gyamfi, 2017).

The TAM has been adopted in STEM education studies to explore the effects of perceived usefulness, ease of use, and fun as predictors of behavioral intention and perceived attitude (Mutambara & Bayaga, 2021; Shiau et al., 2018). The TAM combined with innovation diffusion theory (IDT) has been applied to examine the innovation diffusion of OpenStreetMap in STEM education. The results suggested that STEM students' perception of the usefulness of technology and their perceived attitude toward it leads to their intention to continue using the technology (Shiau et al., 2018). In STEM education in rural areas, the relationship between perceived usefulness and attitude is a critical factor in determining the acceptance of action learning (Mutambara & Bayaga, 2021). Davis (1989) showed that perceived ease of use affects attitude because if users find the system difficult to use, it creates user barriers and affects users' behavioral intentions and attitudes. Additionally, the relationship between the perceived usefulness of technology and intention to use was investigated by studying highly immersive virtual reality systems. However, the research results showed that the perceived usefulness of the system has a weak influence on the intention to use the system (Quaid et al., 2020). Perceived usefulness and attitude are critical for MOOCs' continuance intention; however, it was found that perceived ease of use does not influence attitude (Wu & Chen, 2017). Therefore, we created a second-order construct, perceived usability, that combined the three major constructs of TAM—perceived usefulness, perceived ease of use, and perceived enjoyment—to explore the relationship between perceived usability, attitude, and intention. Thus, the following hypotheses were proposed:

Hypothesis 1 (H1) Perceived usability has a positive and significant effect on attitude.

Hypothesis 2 (H2) Attitude has a positive and significant effect on intention.

Hypothesis 3 (H3) Perceived usability has a positive and significant effect on intention.

Cognitive load

Cognitive load theory was first proposed by a cognitive psychologist based on empirical research on short-term memory ability (Sweller et al., 1998b). Cognitive load has been widely applied in education research since Sweller and colleagues (Sweller et al., 1998b) applied cognitive load to the field of teaching (Chen & Huang, 2020). Cognitive load consists of two constructs: mental load and mental effort. The higher the perception of learners' mental load, mental effort, or task difficulty, the higher the perceived cognitive load for the learning process (Paas, 1992).

The relationship between cognitive load and learning performance has been examined in several previous studies (Chen & Huang, 2020; Liu et al., 2021). Regarding the effect of STEAM-based mobile learning on learning achievement and cognitive load, the research results showed that the learning effectiveness of the experimental group (game-based learning system) was superior to that of the control group, and that the experimental group (game-based system) generated a lower cognitive load than that of the control group (transportation vehicles) (Chen & Huang, 2020). Regarding the effect of cognitive load on learning with augmented reality (AR), learning with 3D technology, and traditional learning, the research results found that the AR group performed better than the 3D and traditional groups in their knowledge improvement, and the AR group students had the lowest cognitive load among the three groups. These results suggest that integrating AR in experiments that help students construct knowledge by providing a virtual–real fusion environment significantly reduces the cognitive capacity that students need to allocate to deal with learning tasks (Liu et al., 2021). Thus, most of the studies that focus on cognitive load theory examine the difference between the experimental and control groups through t-tests, and only a few studies directly explore the connection between cognitive load and STEAM learning intentions.

Additionally, a previous study aimed to identify the factors affecting higher education students' behavioral intention toward learning management systems via the TAM, including perceived usefulness and perceived ease of use, and external factors, including self-efficacy, enjoyment, subjective norms, satisfaction, interactivity, and control. The research results confirmed that the relationships between the influencing factors provided insight into students' behavioral intentions toward the use of learning systems (Findik-Coşkunçay et al., 2018). Therefore, based on the above-mentioned studies, we believe that cognitive load is negatively correlated with learning performance and intention. Additionally, learning intention is positively affected by perceived usefulness, perceived ease of use, and perceived enjoyment. Cognitive load plays a critical role in augmented reality (AR) continuous learning intention. A previous study showed that less cognitive load, stronger motivation, and more positive attitudes towards learning intention in AR (Cheng, 2017). High-quality instructional design enhances the level of germane cognitive load and continuous learning intention (Costley & Lange, 2017). A previous study examined the relationship between perceived cognitive load, motivation, attitudes, perceived usefulness, and learning intention in AR learning. Motivation factors mediated the relationship between learners' cognitive load and learning intention (Cheng, 2017). Thus, the following hypothesis was proposed to examine the connection between cognitive load and STEAM learning intention:

Hypothesis 4 (H4) Cognitive load has a negative and significant effect on perceived usability.

Attention, relevance, confidence, and satisfaction (ARCS) theory

The ARCS model was developed by John Keller to provide an instructional model to explain how to motivate learners and ensure the continuity of motivation during the teaching activity (Keller, 1983). This model has been widely applied in evaluating the motivation of e-learning and digital teaching material design areas in recent decades (Karakış et al., 2016). The ARCS model includes four components: attention, relevance, confidence, and satisfaction (Keller, 1983). Students' attention can be attracted in two ways: (1) perceptual arousal: using amazing or remarkable points of interest to attract students' interest, and (2) inquiry arousal: stimulating students' curiosity by posing challenging questions or problems to be solved (Keller, 2009). Relevance aims to establish relevance regarding the target knowledge in order to increase learners' motivation. Confidence describes the relationship between learners' expectations of success and confidence levels during the learning process. Confidence helps learners understand their likelihood of successful learning and helps them avoid feeling that they cannot finish the learning objectives. Satisfaction aims at learning to be rewarding or satisfying, as a form of achievement. Learners should be satisfied with what they achieve during their learning activities (Keller, 2009). The ARCS theory argues that learners' motivation can be increased if the teaching material satisfies the above-mentioned four components.

The ARCS theory has proven to be an effective tool for enhancing learner motivation and performance (Jason Bond Huett, 2006). The ARCS motivation model was used to investigate the effects of computer-assisted instructional materials designed for the ASSURE model (an instructional system) on students' performance and attitudes in mathematics classes. The research results showed that computer-assisted instructional materials have a positive impact on students' attitudes toward computer-assisted instruction and enhance their academic achievement (Karakış et al., 2016). Keller's (1983) ARCS model was used to examine the effects of the four components on students' attitudes toward the use of gamification for competency development in higher education in Spain. The study revealed that perceived attention, perceived relevance, and perceived confidence directly and positively influence students' attitudes toward using online educational video games to develop competencies (Galbis-Córdoba et al., 2017). A previous study adopted the ARCS model to examine the influence of the gamified learning approach on science learning, achievement, and motivation by using a context-aware mobile learning environment. The ARCS model explains and verifies the effects of the four components on students' motivation and learning achievement (Su & Cheng, 2015). For the problem-based learning (PBL) method, the ARCS model has been used to explore the relationship between learning motivation and entrepreneurial attitudes by focusing on the impact of the PBL method on the learning motivation of entrepreneurial attitudes (Munawaroh, 2020). Thus, the following hypotheses were proposed:

Hypothesis 5 (H5) ARCS has a positive and significant effect on attitude.

Moderation effect

Affective domain assessment for STEAM is one of the most popular assessments for STEM education (Gao et al., 2020). A previous study investigated attitudes, beliefs, motivation, and interest towards the intention of disciplines in STEM. The well-designed STEM activity not only increased students' knowledge, but also increased their affective intention in STEM (Apedoe et al., 2008). The STEM program activities can help students increase their intention and factor in the ARCS model, such as confidence, to improve STEM knowledge and skills. The students' confidence in success in STEM strengthened the effects of perceived usability and attitude (Musavi et al., 2018). The ARCS motivation model reveals the key motivation factors adopted to explain the relationship between learners' perceived usability and improvement of learning attitudes (Chang et al., 2019). Thus, the following hypotheses of moderation effects are proposed:

Hypothesis 6 (H6) Perceived usability positively moderates the relationship between attitude and intention.

Hypothesis 7 (H7) ARCS positively moderates the relationship between perceived usability and attitude.

This study proposed a conceptual research framework that includes three second-order factors derived from TAM (perceived usefulness, perceived ease of use, and perceived enjoyment), ARCS (attention, relevance, confidence, satisfaction), and cognitive load (mental load and mental effort) to explain the continuous learning intention of STEAM education. The proposed conceptual research framework is illustrated in Fig. 3 to address the research objectives.

Method

Population and sample

In this study, elementary and university students were recruited in the classroom after their learning activities. The participants voluntarily participated in the questionnaire survey. Similar participant selection and statistical methods were adopted in a previous study (Mutambara & Bayaga, 2021). A non-probability voluntary response self-selection sampling method was adopted to recruit students following the sampling procedure in a previous empirical study of undergraduate students (Barrett et al., 2021). The present study used two STEAM teaching activities to collect survey data. The data collection period was from February to May 2021, and 145 questionnaire responses were collected, yielding 141 valid responses. Participation in the questionnaire survey was voluntary (84 undergraduate students and 57 elementary students), and the participants completed the questionnaire after STEAM teaching activities.

We developed STEAM learning materials for elementary and college students that suited their level, although

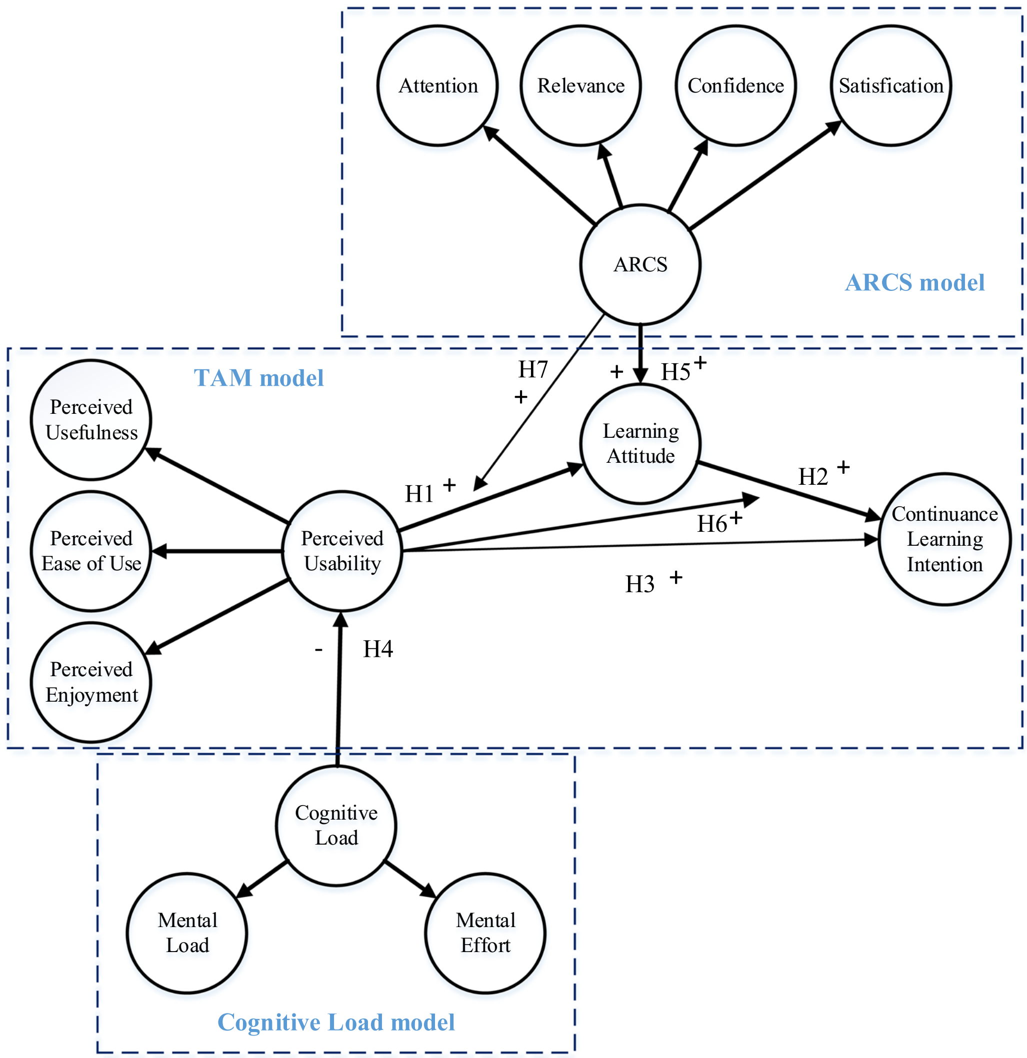

Fig. 3 Conceptual research framework

the experimental equipment used was the same. Since the goal of this study was to investigate participants' continuous learning intention and not the effectiveness of their learning, to collect more samples and encourage more students to participate, we invited these two groups of students to verify our research model. The learning materials used in the study were micro bit and AI neural network programming, which has never been taught to elementary school or college students. The learning activity was designed to be more difficult for college students than for elementary school students. Primarily, the learning materials and activities were designed keeping in mind the difficulty that college students and elementary school students could accept.

We conducted two similar STEAM activities and used the same questionnaire to collect survey data after the STEAM activities in the university and elementary school. The two versions of STEAM activities have the same learning topic with different learning materials: a difficult one for college students and an easier one for elementary students. The participants voluntarily participated in the questionnaire survey. University student participants were 20–24 years old and the elementary school student participants were at the K5–K6 level. Participants from the K5–K6 level were selected because their knowledge level fits the teaching of AI-based knowledge for the syllabus in elementary school. We conducted STEAM learning activities on undergraduate and elementary students because we hoped our research results could have better interpretive results that would be suitable for university and elementary students. The instructions were the same for both the elementary and university students.

Variables

This study integrates three major theories—TAM, cognitive load theory, and ARCS theory—into the proposed STEAM research framework. The research framework consists of 11 constructs that include the learning intention of STEAM as the main construct and a second-order construct. The first part of the main construct was derived from TAM, which included perceived usefulness, perceived ease of use, perceived enjoyment, attitude, and intention. This study created a second-order construct, namely perceived usability, which includes three constructs (perceived usefulness, perceived ease of use, and perceived enjoyment) derived from TAM (Davis, 1989; Davis et al., 1989; Kanchanatanee et al., 2014; Teo, 2009; Weng et al., 2018). The cognitive load theory construct is divided into two sub-constructs: mental effort and mental load (Chen & Huang, 2020). The ARCS theory construct consists of four sub-constructs: attention, relevance, confidence, and satisfaction (SAT) (Karakış et al., 2016; Keller, 1983, 2009; Lin, Chai, et al., 2021). The model constructs, definitions, and references are listed in Table 1.

Design of AI-based STEAM education game and experiment procedure

In this study, STEAM teaching materials contained instructions regarding both STEAM and AI concepts. The STEAM teaching materials used in this study were designed based on the STEAM 6E framework. This six-step framework included engagement, exploration, explanation, engineering, enrichment, and evaluation to complete the STEAM learning task. Using these concepts, students designed an AI-based STEAM game. The game uses computer vision recognition techniques to automatically recognize a user's hand gestures and control a robot to play a game of rock–paper–scissors with users. The details of the game are discussed below.

STEAM concepts

1. Science: The students were required to understand computer vision recognition theory and neural network theory to design and implement a neural network in order to develop an AI-based STEAM rock–paper–scissors game.
2. Technology: The students used Kittenblock, a block-based visual programming language development tool, to code the program for the AI-based STEAM game.

Table 1 Model constructs, definitions, and references

Constructs	Definition	Theory	References
Perceived usefulness	The degree to which a student believes that studying the STEAM teaching materials designed by the researchers would enhance their learning performance	TAM	Davis, (1989); Davis et al., (1989)
Perceived ease of use	The degree to which a learner believes that the STEAM teaching materials ease studying	TAM	
Perceived enjoyment	The extent to which a learner perceives that the STEAM teaching activity in this study is enjoyable	TAM	
Learning attitude	The degree of a learner's attitude toward learning STEAM	TAM	
Learning intention	The degree of a learner's continuance intention of learning STEAM	TAM	
Mental load	The degree of a learner's difficulty of understanding the STEAM materials designed by the researchers of this study	Cognitive load	(Paas, (1992); Paas et al., (2003) (Trujillo, (2019)
Mental effort	The degree of neurocognitive process, that is, the extent of information processing and resource allocation by a student to understand and finish the task in the STEAM teaching activity	Cognitive load	
Attention	The degree of the STEAM learning materials' ability to stimulate curiosity or attract a student's attention	ARCS	Keller, (1983)
Relevance	The degree of relevance of the STEAM learning materials felt by a learner (higher the relevance, the higher the learner's learning motivation)	ARCS	
Confidence	The level of confidence felt by a learner about being able to finish the learning task in the STEAM teaching activity	ARCS	
Satisfaction	The extent to which a learner is pleased or satisfied with the STEAM learning contents	ARCS	

TAM technology acceptance model, *ARCS* attention, relevance, confidence, and satisfaction, *STEAM* science, technology, engineering, arts, and math

3. Engineering: In the process of assembling the game, in addition to understanding the structures of various parts of the micro:bit and motor, students had to use engineering concepts.
4. Arts: The Arts part of our STEAM project required students to design unique graphs on the micro:bit of the AI-based STEAM rock–paper–scissors game. In this study, the lecturer asked students to use their creativity to design the images in the motor, and the graphs denoted the rock, paper, and scissors on the micro:bit LED screen to increase the appeal of the game, as shown in Fig. 5c.
5. Mathematics: Students had to use mathematics to evaluate the correct rate of computer vision recognition tasks for gesture recognition and tune the optimal parameters in the neural network of gesture recognition.

In this study, the learning activity was designed to allow learners to understand image recognition and implement a hardware-controlled (micro:bit + motor) rock–paper–scissors game in 2 weeks. The features of the project are as follows:

Step 1: Obtaining images of scissors, rocks, and paper through the webcam image acquisition program and storing them in the computer.

Step 2: Training an AI deep learning neural network to learn the image features of scissors, rock, and paper from a user's gesture.

Step 3: Coding a program in the Scratch language in the Kittenblock environment that automatically recognizes the user's hand gestures (rock, paper, and scissors) via a webcam.

Step 4: Testing the performance of the gesture recognition system.

Step 5: Tuning of the parameters of the neural network or retraining the neural network model, ensuring the game's best performance.

Step 6: Assembling the micro:bit and motor to complete the game design.

The students were taught to employ the concept of AI to design an intelligent system that could recognize scissors, rocks, and paper expressed in human gestures via a webcam in real time; subsequently, they were taught STEM subjects to create an intelligent system that can automatically recognize the gestures. The program designed for this game determines the player's gestures as either scissors, rock, or paper, and subsequently uses the micro:bit to control the motor to raise the corresponding Lego arm. The learning activities of STEAM + AI are illustrated in Figs. 4, 5.

Data collection procedure

The experimental procedure was conducted over two weeks and organized into the following two procedural stages:

(1) Orientation and teaching

The development of the teaching activities in this study followed the 6E model, wherein the teaching objectives, STEAM knowledge content, and AI concepts were considered. In this model, the teacher plays the role of a guide, while the students are guided by the teacher or the teaching students on how to complete the tasks and produce the learning outcomes at each stage. The teacher taught students how to finish an AI-based STEAM game. The students must

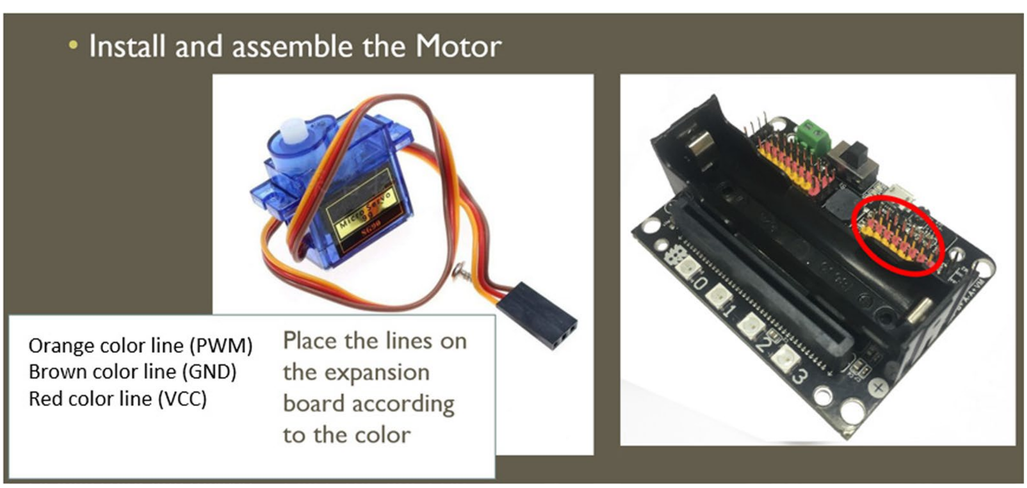

Fig. 4 An illustration of STEAM teaching materials

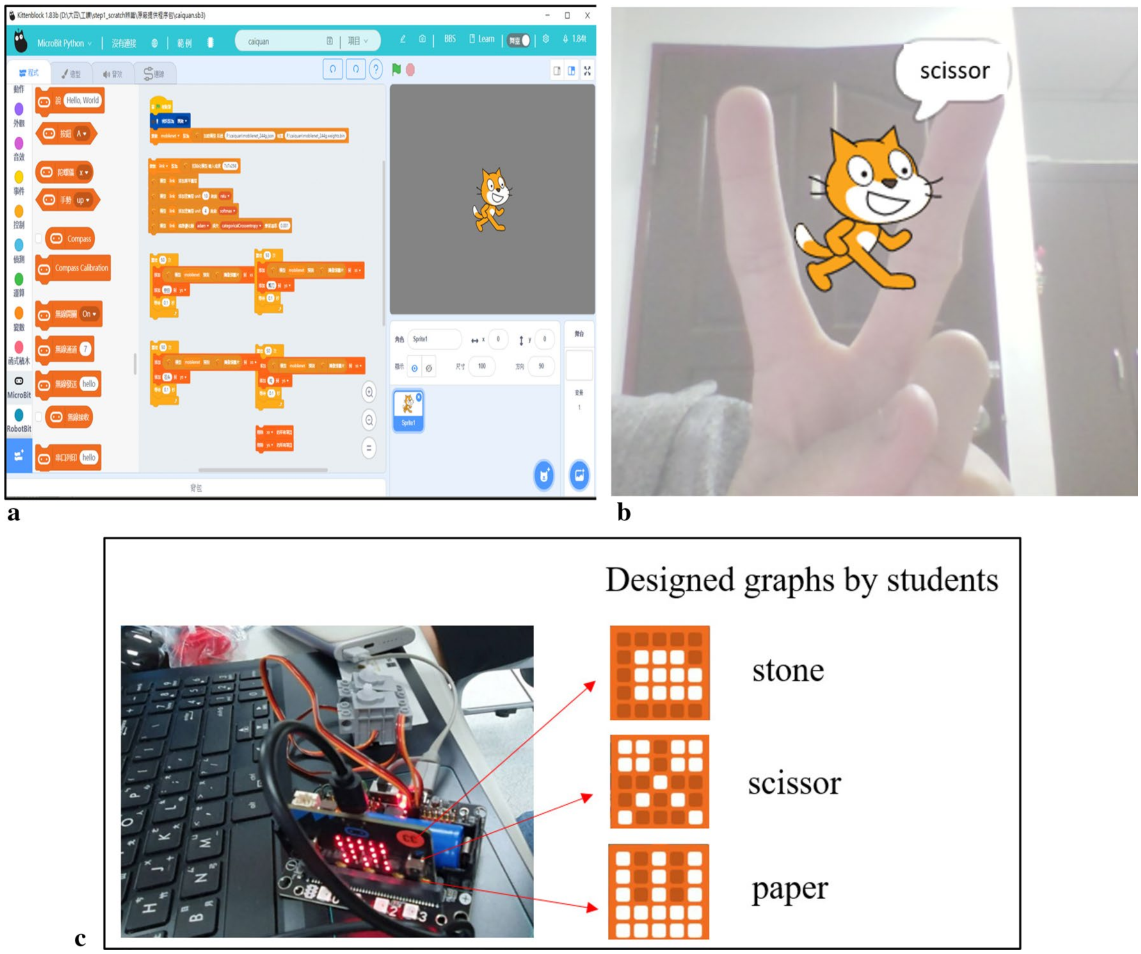

Fig. 5 **a** Coding the program in Kittenblock. **b** AI program can recognize user's gestures (blank,scissors, rock, paper) in real time through webcam image. **c** Designed graphs by students in the STEAM activity

have the ability to design their own AI-based STEAM game by retraining the neural network with their own photos.

(2) Data collection instrument

Participants were asked to complete an online questionnaire designed by the authors of this study. Researchers were available on site to resolve any query of the participants regarding the questionnaire items.

Measurement tools

The questionnaire used in this study included items from the following scales: TAM scale, cognitive load, and ARCS scale. The TAM scale elements used in this study were derived from the scale developed by (Mutambara & Bayaga, 2021), including three major concepts: perceived usefulness, perceived ease of use, and perceived enjoyment. The cognitive load scale, which includes mental load and mental effort, was developed by (Chen & Huang, 2020; Hwang et al., 2013) based on the concepts of cognitive load proposed by Sweller and colleagues (Sweller, 1988; Sweller et al., 1998a). The ARCS scale, which includes items measuring attention, relevance, confidence, and satisfaction of respondents, was developed by (Li et al., 2018) based on Keller's proposed ARCS theory (Keller, 1983, 2009). Thus, an instrument consisting of 24 items (TAM scale), 8 items (cognitive load scale), and 20 items (ARCS scale) rated on a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree") was proposed in this study. Detailed information on each item is presented in Appendix A. The data were imported into the PLS-SEM software to calculate reliability, validity, and structural model estimation. PLS-SEM has been used in education assessment (Olmedo Moreno et al., 2014) and STEM education (Badri et al., 2016; Shiau et al., 2018).

Results

Measurement model assessment

This study adopted confirmatory factor analysis (CFA) to assess the measurement model in terms of convergent

Table 2 Reliability

Construct	Item	Mean	SD	Standardized item loading	Cronbach's alpha	CR	rho_A	AVE	VIF
Perceived usability (USAB)		4.02	0.65		0.96	0.96	0.96	0.67	
Perceived usefulness (PU)					0.95	0.96	0.95	0.82	
	PU1	4.06	0.77	0.92					4.17
	PU2	4.06	0.80	0.92					4.19
	PU3	4.08	0.80	0.91					3.85
	PU4	4.16	0.76	0.89					3.27
	PU5	4.06	0.83	0.90					3.47
Perceived ease of use (PEOU)					0.91	0.93	0.91	0.74	
	PEOU1	3.79	0.79	0.88					3.13
	PEOU2	3.79	0.84	0.87					2.86
	PEOU3	3.90	0.84	0.90					3.41
	PEOU4	4.13	0.75	0.83					2.17
	PEOU5	3.80	0.86	0.81					2.16
Perceived enjoyment (PENJ)					0.90	0.94	0.91	0.84	
	PENJ1	4.23	0.79	0.90					2.57
	PENJ2	4.12	0.76	0.92					2.97
	PENJ3	4.14	0.79	0.93					3.32
Attitude (ATT)					0.93	0.94	0.93	0.77	
	ATT1	4.08	0.76	0.82					2.23
	ATT2	3.82	0.80	0.90					3.60
	ATT3	3.97	0.74	0.88					2.90
	ATT4	3.92	0.78	0.90					3.54
	ATT5	4.04	0.75	0.89					3.13
Intention (INT)					0.89	0.93	0.89	0.82	
	INT1	4.06	0.76	0.90					2.34
	INT2	3.81	0.82	0.89					2.55
	INT3	3.86	0.88	0.92					3.11
Cognitive load (CL)		2.51	0.88		0.94	0.95	0.94	0.72	
Mental effort (ME)					0.90	0.93	0.90	0.77	
	ME1	2.57	0.99	0.91					3.75
	ME2	2.33	1.02	0.92					3.76
	ME3	2.75	1.03	0.85					2.18
	ME4	2.57	1.11	0.82					2.01
Mental load (ML)					0.88	0.92	0.88	0.80	
	ML1	2.61	1.00	0.86					1.91
	ML3	2.43	1.06	0.92					3.18
	ML4	2.32	1.05	0.91					2.94
ARCS		3.97	0.64		0.97	0.97	0.97	0.67	
Attention (ATN)					0.93	0.95	0.93	0.78	
	ATN1	4.02	0.74	0.88					3.07
	ATN2	4.05	0.74	0.89					3.12
	ATN3	4.13	0.73	0.86					2.83
	ATN4	4.10	0.80	0.89					3.65
	ATN5	4.12	0.73	0.90					3.58
Relevance (REV)					0.89	0.93	0.89	0.76	
	REV1	4.01	0.73	0.88					2.61
	REV2	4.04	0.73	0.86					2.39
	REV3	3.85	0.83	0.89					3.04

Table 2 (continued)

Construct	Item	Mean	SD	Standardized item loading	Cronbach's alpha	CR	rho_A	AVE	VIF
	REV4	3.77	0.84	0.85					2.49
Confidence (COF)					0.93	0.95	0.93	0.78	
	COF1	3.84	0.81	0.91					4.20
	COF2	3.85	0.85	0.89					3.81
	COF3	3.75	0.86	0.86					2.87
	COF4	3.94	0.82	0.88					3.25
	COF5	3.84	0.86	0.88					3.25
Satisfaction (SAT)					0.90	0.94	0.90	0.83	
	SAT1	4.05	0.75	0.91					2.74
	SAT4	4.13	0.74	0.92					2.95
	SAT5	4.05	0.82	0.91					2.77

SD standard deviation, *CR* composite reliability, *AVE* average variance extracted, *VIF* variance inflation factor

validity and reliability (Findik-Coşkunçay et al., 2018). Table 2 summarizes the mean, standard deviation, standardized factor loadings, Cronbach's alpha, composite reliability (CR), rho_A, average variance extracted (AVE), and variance inflation factor (VIF). All factor loadings were above 0.60 and at a significance level of $p < 0.001$, which revealed convergent validity (Liu, 2020). Each observed variable must have a factor loading > 0.7 to provide adequate convergent validity (Hair et al., 2006). The Cronbach's alpha coefficients for each construct were as follows: perceived usability (0.96), perceived usefulness (0.95), perceived ease of use (0.91), perceived enjoyment (0.90), attitude (0.93), intention (0.89), cognitive load theory (0.94), mental effort (0.90), mental load (0.88), ARCS (0.97), attention (0.93), relevance (0.89), confidence (0.93), and satisfaction (0.90). They all satisfied the criterion of alpha > 0.7 (Dörnyei & Taguchi, 2009). The CR values of all constructs were greater than the suggested minimum of 0.7, all rho_A values were greater than 0.9, and all AVE values were greater than 0.5. All constructs in the measurement model satisfied the reliability criterion, and rho_A values of three constructs (intention, mental load, and relevance) were slightly lower than 0.9. This study used VIF to examine whether multicollinearity existed. The results demonstrated that all VIF values were acceptable (VIF < 5), indicating that the study data had no serious multicollinearity (Galeazzo et al., 2021). Because the factor loadings of item 5 of relevance, and items 2 and 3 of satisfaction did not have adequate VIF values (< 5) on the related latent variables, these items were extracted from the model. Therefore, all values exceeded the minimum threshold, indicating that the constructs were explained (Hair et al., 2006, 2016).

Discriminant validity is measured by the square root of the AVE of each latent variable, which indicates that each construct's correlation is higher than the other constructs' correlations (Peter, 1981). Table 3 shows the discriminant validity. The results support the discriminant validity of all the measured constructs in this study. Additionally, recent research (Henseler et al., 2015; Voorhees et al., 2016) suggests that the heterotrait–monotrait (HTMT) criterion could be better than the traditional Fornell and Larcker metric (Fornell & Larcker, 1981). The values of the HTMT criterion use the mean value of the item correlations across constructs relative to the geometric mean of the average correlations for the items measuring the same construct (Barrett et al., 2021). The results of HTMT inference at the 95% confidence level were obtained by conducting a bootstrapping procedure with a sample size of 5000. All HTMT values in Table 4 were less than 1, supporting and confirming discriminant validity (Hair et al., 2016).

Structural model assessment

This study employed partial least squares (PLS) using SmartPLS software to estimate the parameters of the proposed model. The multi-step procedure followed Baron and Kenny's (1986) method to test the direct, indirect, and mediation effects of the variables. The estimation method utilized 5000 bootstrapping resampling estimations to examine the robustness of the research findings at the 95% confidence level. The structure of the proposed research model was examined by calculating the path coefficient values to assess the statistical significance of each hypothesis. Figure 6 shows the estimated path coefficients.

H1 Perceived usability has a positive and significant effect on attitude.

Table 3 Fornell–Larcker discriminant validity results

Construct	PU	PEOU	PENJ	ATT	INT	ML	ME	ATN	REV	COF	SAT
Perceived usability (USAB)											
Perceived usefulness (PU)	**0.91**										
Perceived ease of use (PEOU)	0.74	**0.86**									
Perceived enjoyment (PENJ)	0.84	0.69	**0.92**								
Learning attitude (ATT)	0.78	0.73	0.80	**0.88**							
Learning intention (INT)	0.78	0.74	0.76	0.80	**0.90**						
Cognitive load (CL)											
Mental load (ML)	− 0.28	− 0.32	− 0.27	− 0.30	− 0.20	**0.90**					
Mental effort (ME)	− 0.27	− 0.30	− 0.28	− 0.26	− 0.19	0.85	**0.87**				
ARCS theory											
Attention (ATN)	0.77	0.70	0.81	0.80	0.85	− 0.21	− 0.22	**0.88**			
Relevance (REV)	0.76	0.75	0.71	0.75	0.81	− 0.20	− 0.19	0.84	**0.87**		
Confidence (COF)	0.76	0.74	0.73	0.78	0.80	− 0.26	− 0.27	0.76	0.82	**0.88**	
Satisfaction (SAT)	0.77	0.66	0.81	0.78	0.80	− 0.21	− 0.24	0.83	0.79	0.75	**0.91**

The bold values are the square root of the AVE of each latent variable

Table 4 Heterotrait–monotrait ratio (HTMT)

	PU	PEOU	PENJ	ATT	INT	ML	ME	ATN	REV	COF	SAT
Perceived usability (USAB)											
Perceived usefulness (PU)											
Perceived ease of use (PEOU)	0.80										
Perceived enjoyment (PENJ)	0.91	0.76									
Learning attitude (ATT)	0.83	0.79	0.87								
Learning intention (INT)	0.85	0.82	0.85	0.87							
Cognitive load (CL)											
Mental load (ML)	0.30	0.36	0.29	0.33	0.23						
Mental effort (ME)	0.28	0.33	0.31	0.28	0.21	0.96					
ARCS theory											
Attention (ATN)	0.82	0.75	0.88	0.86	0.93	0.23	0.24				
Relevance (REV)	0.82	0.83	0.78	0.82	0.90	0.22	0.20	0.91			
Confidence (COF)	0.81	0.80	0.79	0.83	0.88	0.29	0.29	0.82	0.90		
Satisfaction (SAT)	0.84	0.72	0.90	0.85	0.89	0.22	0.25	0.91	0.88	0.82	

H2 ARCS positively moderates the relationship between perceived usability and attitude.

H3 Perceived usability has a positive and significant effect on intention.

H4 Cognitive load has a negative and significant effect on perceived usability.

H5 ARCS has a positive and significant effect on attitude.

H6 Perceived usability positively moderates the relationship between attitude and intention.

H7 ARCS positively moderates the relationship between perceived usability and attitude.

The direct path coefficients of the structural model were analyzed to examine the relationships between the constructs (see Fig. 6). According to the results of the structural model in Table 5, significant positive relationships were found between constructs H1, H2, H3, and

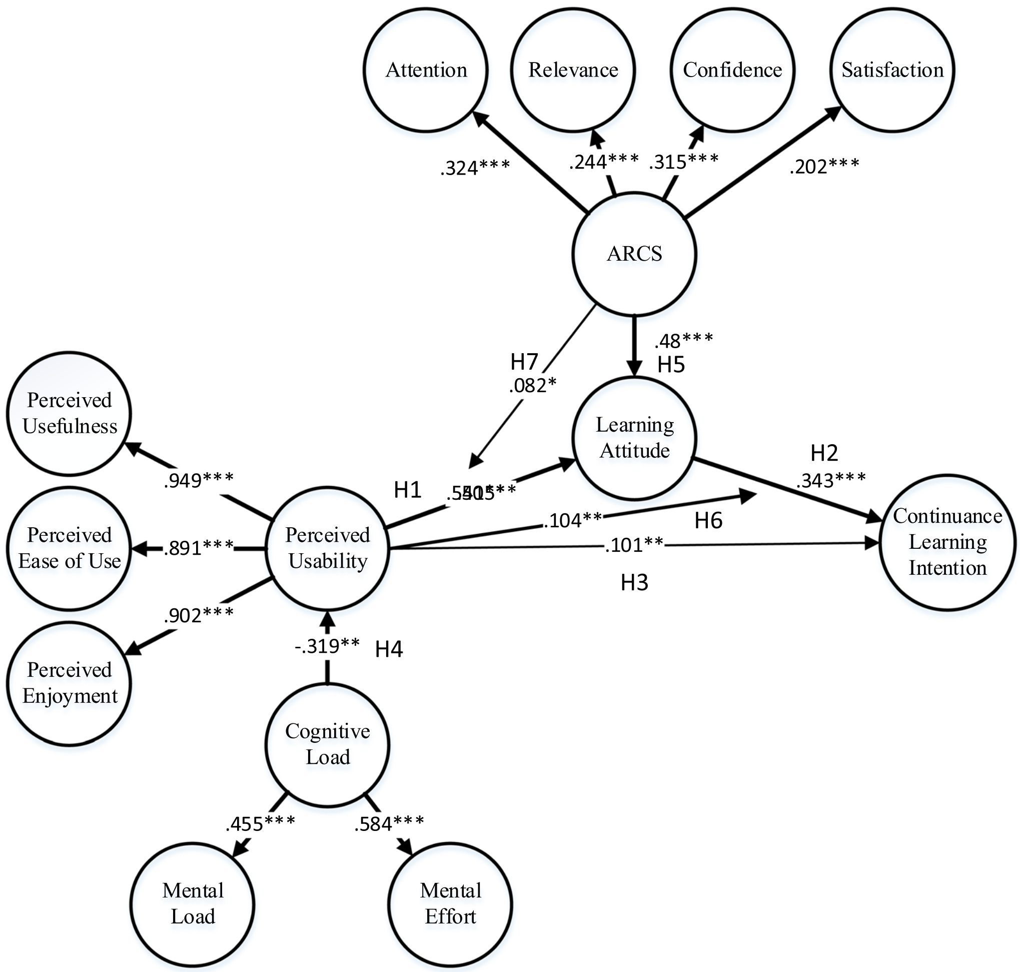

Fig. 6 Structural model

Table 5 Summary of structural model analysis

	Path coefficients	|*t*|	*p*-value	Outcome	R^2	f^2	q^2	95% CILL	95% CIUL
H1:USA *B*→ ATTITUDE	0.41	2.45	0.014	Supported	0.75	0.15	2.37	0.04	0.69
H2:ATTITUDE→ INTENTION	0.34	3.54	0.000	Supported	0.74	0.14	2.30	0.15	0.53
H3:USA *B*→ INTENTION	0.55	5.92	0.000	Supported	0.74	0.35	1.47	0.36	0.72
H4:Cognitive Theory→ USAB	−0.32	3.27	0.001	Supported	0.10	0.11	−0.01	−0.50	−0.12
H5:ARCS→ ATTITUDE	0.48	3.09	0.002	Supported	0.75	0.20	2.15	0.21	0.84

Model fit: SRMR = 0.069, RMS_theta = 0.16

ARCS ARCS theory, *USA B* perceived usability, *CILL* confidence interval lower limit, *CIUL* confidence interval upper limit

H5 at the level of $p<0.05$. Additionally, regarding the cognitive load theory construct (H4), a strong negative relationship was found between perceived usability and cognitive load. Analysis of the coefficient relationships within the original TAM constructs in STEAM education demonstrated that all TAM constructs proposed by Davis were supported (Davis, 1989); H1 (perceived usability→learning attitude) path showed a significant positive effect ($B=0.41$, $p<0.005$), H2 (learning attitude→learning intention) path showed a strong significant effect ($B=0.34$, $p<0.01$), and H3 (perceived usability→learning intention) path showed a significant positive effect ($B=0.55$, $p<0.01$). The results revealed that high perceived usability (including perceived usefulness, perceived ease of use, and perceived enjoyment) enhanced learning attitude, and learning attitude positively influenced learning intention. Analysis of the effects of cognitive load (H4) (cognitive load → perceived usability) showed that the variable had significant negative direct effects on perceived usability ($B=-0.32$, $p<0.01$). The results revealed that the lower the cognitive load, the higher the perceived usability of STEAM education. Regarding the effects of Keller's ARCS theory, H5 (ARCS → learning attitude) showed a positive and significant effect ($B=0.48$, $p<0.01$). The results indicate that strong ARCS motivation positively influences learning attitudes in STEAM education.

The coefficient of determination (R^2) measures the in-sample predictive power (Hair et al., 2016). The f^2 effect determines the change in the R^2 value when a specified exogenous construct is omitted from the model in the range of 0.02, 0.15, and 0.35, indicating an exogenous construct's small, medium, or large effect, respectively (Hair et al., 2016). The q^2 value determines the impact of the model's exogenous constructs on their reflective endogenous constructs. For PLS prediction, the Q2 prediction value for all indicators was above 0, indicating that the structural model has predictive power (Pangarso et al., 2020). Therefore, the R^2, f^2, and q^2 values (Table 5) showed that our structural model had a medium predictive power.

The standardized root mean square residual (SRMR) is a goodness-of-fit measure for PLS-SEM that measures the mean absolute value of the covariance residuals by transforming both the sample covariance matrix and the predicted covariance matrix into correlation matrices (Hair et al., 2016). RMS_theta is the root mean squared residual covariance matrix of the outer model residuals (Lohmöller, 1989). The goodness-of-fit measures, SRMR and RMS_theta, should be less than 0.08 and close to 0, respectively (Hair et al., 2016). The SRMR value for the saturated model was 0.069, and the RMS_theta value was 0.16 close to 0, indicating a well-fitting model in this study.

Table 6 Moderating effect test results

	Original sample	*t*-value	*p*-value	Outcome
H6: USAB x ATT → INT	0.104	3.13	0.002**	Supported
H7: ARCS x USAB → ATT	0.082	2.03	0.042*	Supported

USA B perceived usability, *ATT* = attitude, *ARCS* ARCS theory; INT = intention

*$p<0.05$; ** $p<0.01$

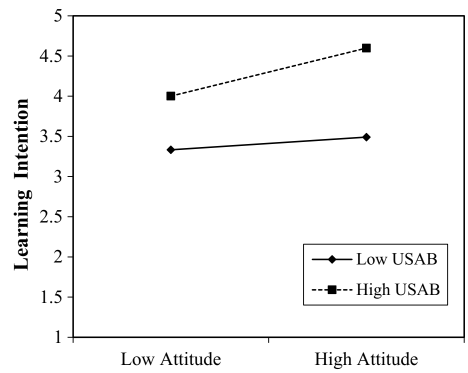

Fig. 7 Moderating effect of perceived usability (USAB) on the relationship between learning attitude and learning intention.

Moderating effect analysis

Subsequently, we examined the moderating effects of these variables. The results in Table 6 show that the interaction term "perceived usability x attitude" is positive and significant for intention ($B=0.104$, t-value = 3.13, $p=0.002$), and the interaction term "ARCS x perceived usability" is positive and significant for attitude ($B=0.082$, t-value = 2.03, $p=0.042$). To reveal the moderating effects of intention and attitude more intuitively, this study plotted two interactive relationships.

According to the results of the moderating effect of perceived usability (see Fig. 7), the degree of positive influence (slope) of "perceived usability" on the relationship between learning attitude and learning intention at different levels (high and low) is significantly different.

Perceived usability strengthens the positive relationship between attitude and intention. The relationship of "learning attitude → learning intention" is stronger when perceived usability is high; the relationship of "learning attitude → learning intention" is weaker when perceived usability is low. In other words, in the case of a high level of perceived usability, the intention of STEAM learning may be enhanced by a higher awareness of usability. Conversely, when learners' awareness of usability is low, the effect of attitudinal enhancement of STEAM learning intention is lower. Therefore, teachers should consider how to design STEAM teaching materials to enhance students' cognitive usability and attitudes, which in turn will enhance their learning intentions.

According to the results of the ARCS moderating effect (see Fig. 8), the degree of positive influence (slope) of "ARCS theory" on the relationship between perceived usability and attitude at different levels (high and low) is significantly different.

Perceived ARCS strengthens the positive relationship between perceived usability and attitude. When learners'

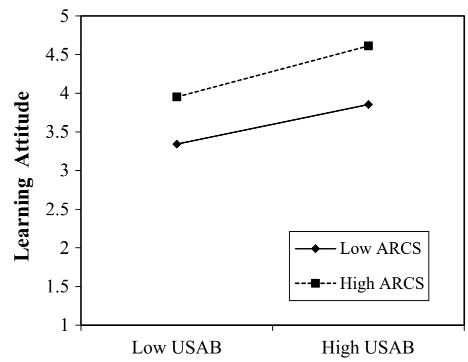

Fig. 8 Moderating effect of the ARCS theory (ARCS) on the relationship between perceived usability (USAB) and learning attitude

perceived ARCS values were high, the "perceived usability → attitude" relationship was stronger; when the perceived ARCS values were low, the "perceived usability → attitude" relationship was weaker. In other words, when learners perceive a high level of ARCS regarding STEAM materials, the "perceived usability → attitude" relationship may be enhanced by the higher ARCS. Conversely, when learners perceive a low level of ARCS, the effect of perceived usability on learning attitudes is lower. Therefore, teachers should focus on designing instruction and/or instructional materials for ARCS to solve the particular motivational problem to enhance learners' perceived usability (Chang et al., 2019) and improve their learning attitudes.

Multi-group analysis

The multi-group analysis allows us to test if our two types of student data groups have significant differences in their group-specific parameter estimates (e.g., outer weights, outer loadings and path coefficients) of our research structural model. The partial least squares multi-group analysis (PLS-MGA) method is a non-parametric significance test for the difference of group-specific results that builds on PLS-SEM bootstrapping results (Matthews, 2017). The PLS-GMA result showed that all hypotheses in our structural model have no significant difference between elementary student group and university group as shown in Table 7. Therefore, our research result can be interpreted as generalization for both elementary and university students.

Discussion

In this study, perceived usability (perceived usefulness, perceived ease of use, and perceived enjoyment) strongly and positively dominated learning attitudes and learning intentions. Additionally, positive learning attitudes influence STEAM learning intentions (Barrett et al., 2021; Mutambara & Bayaga, 2021; Shiau et al., 2018). The research results confirmed the relationship in Davis's TAM constructs (Davis, 1989; Davis et al., 1989) that were applied to explain the behavioral intention of STEAM education (Mutambara & Bayaga, 2021; Su, 2019). This may be because the higher the learners' perceived usability regarding STEAM education, the stronger their attitude toward their learning intention, in line with Bloom's (1956) affective domain argument (Krathwohl et al., 1973).

In this study, ARCS motivation factors (attention, relevance, confidence, and satisfaction) strongly and positively influenced learning attitudes ($B = 0.48$, $p < 0.001$), confirming the relationship in previous studies (Galbis-Córdoba et al., 2017; Ngah et al., 2021). Most previous studies examined the relationship between ARCS and learning performance (Su & Cheng, 2015) or motivation (Wahyudi et al., 2017). This study examined the relationship between ARCS motivation factors and learning attitudes. As ARCS is a model used by the students to solve the problems based on the way they construct knowledge about the concept provided by the teacher, it can show the motivation of the students derived from external conditions. (Wahyudi et al., 2017). The results

Table 7 Multi-group analysis by PLS-MGA method

Hypotheses		Difference (elementary vs. university)		
		Difference Path Coeff	*p*-value original	*p*-value new
H1:	Perceived usability—> attitude	0.261	0.187	0.373
H2:	Attitude—> intention	− 0.243	0.909	0.182
H3:	Perceived usability—> intention	0.246	0.088	0.175
H4:	Cognitive load—> perceived usability	0.034	0.440	0.880
H5:	ARCS—> attitude	− 0.283	0.822	0.356
H6:	Perceived usability Moderating effect (attitude—> intention)	0.077	0.144	0.289
H7:	ARCS moderating effect (perceived usability—> attitude)	− 0.112	0.890	0.220

Coeff. denotes coefficient

of this study confirmed that the affective domain in Bloom's (1956) taxonomy concerns the growth in feelings and attitudes; in other words, motivation enhances learning performance (Krathwohl et al., 1973).

Conversely, learners' cognition had strong and negative effects on perceived usability ($B = -0.319$, $p < 0.01$), in line with previous studies (Findik-Coşkunçay et al., 2018). Cognitive load, including mental load and mental effort, denotes resource allocation for cognitive processing in learning tasks. Mental load represents the cognitive capacity required to process the complexity of a task, whereas mental effort reflects a learner's cognitive capacity or resources that are allocated to complete the learning task (Liu et al., 2021). The high-level load of cognitive processes (such as knowledge recall, comprehension of understanding, application, and analysis) decreases perception, which is consistent with Bloom's (1956) cognitive domain argument of knowledge development of intellectual skills. Therefore, STEAM educators should design teaching materials to decrease learners' cognitive load in order to improve their perceived usability.

Surprisingly, this study found two significant moderating effects that were observed in only a few previous studies. Perceived usability moderated the relationship between learning attitudes and learning intentions. The moderation effect provides further information that a high level of perceived usability strongly enhances the attitude toward the intention of STEAM learning than that of a low level of perceived usability. ARCS motivation further strengthens the positive relationship between perceived usability and learning attitude. Additionally, the research results showed two mediation effects for STEAM learning attitude and learning intention.

A previous study stated that in a highly competitive education system, using SEM analysis is not only helpful in understanding both the consequences and sequences of learning performance, but also provides a boosted understanding of individual learning processes, which are simultaneously shown as a set of complex learning environments within individuals and a meaning of moderate or mediate effects (Horng et al., 2020; Sam Liu, 2017). The results show that cognitive load enables learners to easily understand and implement the STEAM task, which extends the findings of Weng et al. (2018), who found that cognitive load is driven by inherent complexity and deters valuable cognitive resources towards tasks irrelevant to learning.

Conclusions

The research results provide sufficient evidence to other educators in Asia, especially regarding the lack of student attention in the digital era, which disturbs students' engagement with digital education. This study found that in ARCS and perceived usability, the influence of students' learning attention was mediated by learning attitudes. A similar observation was made regarding ARCS; that is, ARCS positively significantly influenced perceived usability and strengthened its effects on learning attitudes. Our research results supported ARCS learning, which reflects several critical characteristics of STEAM, including cross-domain and hands-on learning, life application, problem solving, and sense learning, and applied such concepts to an AI-based task (Li et al., 2018). Thus, these findings should help educators recognize the importance of AI-based education and 'playfulness' in learning, and help them combine AI concepts with their teaching strategies to enhance students' learning attitudes and explore learning opportunities. The findings of this study have various implications for helping students become familiar with micro:bit and AI-based learning that assists them in developing their abilities, skills, and beliefs to predict their future careers (Zhu et al., 2019). The potential theoretical and educational implications are explained in the following section.

Theoretical and educational implications

This study makes several valuable contributions to the literature. First, while previous research on AI-based course design has been conducted in Western countries because of more advanced technology and widely accepted AI concepts, this has not been the case in Asian regions because of the lack of development in technology and economic support, most higher education institutions still remain in the transitional education phase (Adukaite et al., 2017). In the current education scenario, implementing AI concepts for education and gamified learning could not only encourage students' participation and engagement, but also add value to the literature on education (Tan & Cheah, 2021). This is especially the case for research design in higher education institutions, where current research on TAM of STEAM instruction is sparse (Maskeliūnas et al., 2020), specifically affecting the benefits of digital learning. Second, this study provides new perspectives for demonstrating how to use AI and digital learning in formal educational environments that have limited technological infrastructure, but which could be interesting and enjoyable despite this limitation by adjusting students' attitudes toward learning intention. Third, this study incorporated a modified integrated model of the mediation–moderation mechanism. In the mediation mechanism, learning attitudes acted as mediating variables. This mediating effect was examined using the bootstrapping technique, which extends the existing education literature (Loughlin-Presnal & Bierman, 2017). The most critical aspect of this study is the use of second-order factors derived from ARCS and the use of perceived usability as a moderating variable, which has not been used in previous digital learning and education studies.

Further, the mediated-moderation model provides more meaningful and insightful information for the education literature (Horng et al., 2020). Therefore, the modified integrated model used in this study makes a critical contribution to the digital learning education literature and provides a foundational reference for future studies, while adding value to the existing research.

Moreover, several educational implications of the study results were identified for educators. First, samples were collected from undergraduates and elementary students in Taiwan. It provides sufficient evidence to other educators in Asia, especially regarding the lack of student attention in the digital era that disturbs students' engagement with digital education (Huang et al., 2006). To harness the positive impact of AI and implement gamification learning design to develop students' intention for learning, educators need to educate students on how to use micro and AI learning tools to enhance their learning interest (Mutambara & Bayaga, 2021). Second, this study found that in ARCS and perceived usability, the influence of students' learning attention was mediated by learning attitudes. Micro:bit and AI-based lessons may not only improve students' attitudes to increase the effectiveness of ARCS motivational strategies, but also help improve students' ability to work in an AI-empowered society in the future (Li & Moore, 2018). Third, the findings also provide insights into cognitive theory and extend the education design of micro- and AI-based curricula. The findings of this study have various implications, from helping students become familiar with micro- and AI-based learning that assists them in developing their abilities, skills, and beliefs to predicting their future careers (Zhu et al., 2019). In this study, cognitive load was negatively correlated with learning performance and intention. This result supports instructors' efforts to guide students in navigating unfamiliar STEAM learning processes, as this unfamiliarity might contribute to learning pressure, consequently decreasing learning performance. Thus, in order to enhance students' learning and decrease their cognitive load, educators should design motivation incentive mechanisms to attract students' interest along with less cognitive load to enhance their learning achievement.

Limitations and future research suggestions

Despite the contributions of this study, several limitations remain to be addressed. First, due to time limitations and lack of sufficient course support, the present study included a sample of students from only one region of Taiwan. A previous study suggested that collected data from different regions provide meaningful and accurate predictions of student learning behavior (Horng et al., 2020). Thus, future research may extend the results of the present study by including students from different regions in Taiwan (e.g., South, North, Middle, and offshore islands of Taiwan). Second, the cultural background of the study was another concern. In the "Western" education system, teachers dedicate a significant amount of time and shoulder responsibilities to guide students to include self-determination in their learning, which is different than the "Eastern" education system (Koul & Fisher, 2005). Thus, future studies may collect samples from different cultural backgrounds and provide a comparative study to extend the findings of this study. Third, the long-standing unsolved problem of AI-based education in STEM studies and employability needs to be considered with other possible variables to examine the hypotheses in future studies (Chu et al., 2019).

Appendix A

Item	Question
Perceived usefulness (PU) (Mutambara & Bayaga, 2021)	
PU1	Using micro:bit + AI learning in class will improve my willingness to participate
PU2	Using micro:bit + AI to learn STEM will improve my learning effect
PU3	Using micro:bit + AI would make it easier for me to learn STEM
PU4	I will find micro:bit + AI useful in learning STEM
PU5	Using micro:bit + AI to learn STEM will improve my learning interest
Perceived ease of use (PEOU) (Mutambara & Bayaga, 2021)	
PEOU1	It will be easy to learn how to use micro:bit + AI learning to learn STEM
PEOU2	I will find it easy to use micro:bit + AI learning to learn STEM
PEOU3	I will find micro:bit + AI learning easy to use in STEM classes
PEOU4	I will find micro:bit + AI learning to be flexible to interact
PEOU5	It will be easy for me to become skillful using micro:bit + AI
Perceived enjoyment (PENJ) (Mutambara & Bayaga, 2021)	
PENJ1	Learning this curriculum will be enjoyable

Item	Question
PENJ2	I will find learning STEM using micro:bit + AI learning fun
PENJ3	I will find using micro:bit + AI learning interesting
Attitude (ATT) (Mutambara & Bayaga, 2021)	
ATT1	I believe it is beneficial to learn STEM
ATT2	I feel positive about learning STEM
ATT3	My experience of learning STEM will be good
ATT4	I like to learn STEM-related subjects
ATT5	Learning about STEM-related subjects will be a pleasant experience
Intention (INT) (Mutambara & Bayaga, 2021)	
INT1	Assuming I have access to micro:bit + AI, I intend to use it to learn STEM
INT2	I am planning to use micro:bit + AI to learn STEM
INT3	I would like to use micro:bit to learn STEM in the future
ARCS	(Li et al., 2018)
Attention (ATTEN)	
ATTEN1	The curriculum can arouse my exploratory motivation
ATTEN2	I can concentrate on curriculum content
ATTEN3	The technique for AI in interactive image recognition attracts my attention
ATTEN4	I will find it fun to program game code for AI in the interactive image recognition
ATTEN5	I will find it fun to interact with micro:bit + AI flexibly
Relevance (REV)	
REV1	STEM teaching resources will be helpful
REV2	I can understand this curriculum
REV3	I can apply the outcome of this practice to different fields
REV4	I can apply the outcome of this practice to various industries (e.g., education and marketing)
REV5	I can apply the outcome of practice to different products
Confidence (COF)	
COF1	I am confident I will succeed in the curriculum content of STEM learning
COF2	I have confidence that I will finish the assignment in the curriculum
COF3	It is not difficult to complete this project
COF4	I am confident in finding other functions
COF5	If I work hard, I can perform well in other systems

Item	Question
Satisfaction (SAT)	
SAT1	I like this type of STEM course. I will continue to study related courses
SAT2	I am very satisfied that I will be able to glean relevant knowledge from the course
SAT3	I am very happy to complete the game in the course material
SAT4	I think it is fun while learning
SAT5	I had a sense of accomplishment in micro:bit + AI and program coding
Cognitive Load (Chen & Huang, 2020)	
Mental Load (ML)	
ML1	The learning content in this activity was difficult for me
ML2	I had to put a lot of effort into answering the questions in this learning activity
ML3	It was troublesome for me to answer the questions in this learning activity
ML4	I felt frustrated answering the questions in this learning activity
Mental Effort (ME)	
ME1	I did not have enough time to finish the project
ME2	During the learning process, the curriculum content caused a lot of stress
ME3	During the learning activity, the content or information required a lot of mental effort
ME4	The curriculum content was difficult to follow and understand

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