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Exploring the effect of improved learning performance: A mobile augmented reality learning system

Wei-Tsong Wang[1] · Ying-Lien Lin[1] · Hsin-En Lu[1]

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Abstract
Students are commonly in a high cognitive load state when they encounter sophisticated knowledge. Whether the novel augmented reality (AR) technology can be utilized in an online learning course to explain complicated scientific concepts in a more understandable manner to students during the COVID-19 period is an unaddressed issue. This study aims to investigate the influences of reducing the physical touch or face-to-face teaching/learning practices via using mobile augmented reality learning systems (MARLS) on students' perceived learning effectiveness. The information feedback viewpoint, flow theory, and cognitive load theory are integrated to examine the effects of the information feedback of MARLS on students' learning effectiveness. This study recruited 204 participants from ten universities to complete a learning task via a MARLS and fill out a questionnaire to collect data for the proposed research model. The empirical results revealed information feedback positively and significantly affected flow experience, perceived learning effectiveness, and continued intention. The improved learning performance of learners was positively related to their continued intention. Also, the extraneous cognitive load negatively and significantly moderated the relationship between information feedback and perceived learning effectiveness. This study proposes meaningful implications and suggestions for future research based on the findings of this experiment.

Keywords Extraneous cognitive load · Flow experience · Information feedback · Perceived learning effectiveness · Continued intention · Improved learning performance

✉ Wei-Tsong Wang
wtwang@mail.ncku.edu.tw

Ying-Lien Lin
r38021019@gs.ncku.edu.tw

Hsin-En Lu
sinen0108@gmail.com

[1] Department of Industrial and Information Management, National Cheng Kung University, No.1, University Road, Tainan City 701, Taiwan, Republic of China

1 Introduction

Using digital technologies, such as augmented reality (AR), has covered a wide field of instructional and learning approaches during COVID-19. AR is a frequently utilized tool via simulating or authentic scenarios to combine complex conceptions and vague images to clarify teaching/learning materials. AR allows learners to follow the information feedback to complete their learning activities supported by the interactive formats of visual or tactile related information to achieve the learning objectives. *Information feedback* is defined as the already evaluated/corrected and provided information transmitted to learners based on their learning processes and outcomes by AR applications (Liu et al., 2021). AR-based learning is ubiquitous in various digital applications, including photographs, games, and other means, enhancing the effectiveness of the learning experience (e.g., Bressler et al., 2013; Demitriadou et al., 2020; Ibáñez et al., 2014; Lai et al., 2019; Shin, 2019). The users do not necessarily possess knowledge of in-depth and broad digital technologies. Generally, AR-based learning applications often assist learners to obtain knowledge by offering them reliable guidance or materials (e.g., information feedback), which is relatively more interesting and diverse than the traditional teaching approach (Bressler et al., 2021; Chang et al., 2022).

The AR-based learning applications may help learners understand abstract concepts and reduce their misperception of the learning materials and extraneous cognitive overload through offering high-quality information feedback (Nikou et al., 2022). *Extraneous cognitive load* refers to how information is presented to an individual, which can result in the need for the individual to devote additional efforts to learning it (Liao et al., 2019; Sweller, 1994). Research indicates that more studies are needed to further investigate whether learning applications supported by different technologies (e.g., AR, three-dimensional (3D), fingertip-movement-based interactions, virtual/computing object) or interactive approaches can enhance learners' learning outcomes because most AR-supported virtual or real-world interactive learning activities rarely provide users with timely and informative feedback when they make mistakes in order to facilitate effective learning (Alhonkoski et al., 2021; AlNajdi et al., 2020; Wang et al., 2022; Westerfield et al., 2015; Yu et al., 2019). Faqih and Jaradat (2021) also state that more AR-related studies regarding user/learner adoption of AR applications are needed because AR applications enable students to think more creatively to understand learning content after the Covid-19 pandemic. Nevertheless, studies that investigate this research issue based on the information feedback perspective are scarce. Additionally, AR-based learning processes may involve the interactions among the use of various information feedback, the formation of human cognition, and the resulting learning effectiveness in an immersing learning situation based on a flow experience perspective, while the research findings may not always generate a positive learning performance or experience in the literature of other research contexts (e.g.,Karelaia & Hogarth, 2008;

Lerch & Harter, 2001; Lin & Wang, 2021). *Flow experience* refers to an individual psychological or motivational state of complete focused attention, sense of control, and enjoyment of a given learning task, facilitating their cognitive capacities (e.g., Csíkszentmihályi, 1990; Hohnemann et al., 2022). Regarding the learners' cognitive capacity, learners who need to accomplish both visual and tactile tasks may need to put additional efforts into the learning process, which may negative affect their learning effectiveness if the tasks were not appropriately designed.

Based on cognitive load theory, AR-based learning must give adequate feedforward that may reduce the formation and increase extraneous cognitive loads when an individual attempts a task. Therefore, the level of learners' perceived learning effectiveness is generally high when they sense the learning tasks include an appropriate level of challenges (Chang, 2018; Hamari et al., 2016). *Perceived learning effectiveness* refers to the learning results of learners regarding the formative and summative evaluations. Accordingly, extraneous cognitive load may increase the capacity of individuals working memories (i.e., knowledge, skills, and abilities) when the work/learning processes involve high levels of task complexity. Individuals' high level of working memories might inhibit their work/learning effectiveness (Martin et al., 2020; Song & Sparks, 2019; Sweller et al., 1998).

In this study, mobile augmented reality learning systems (MARLS) are referred to as mobile-based learning applications that include designing text, video content, and fingertip-to-contact screen to rotate the 3D graphics and can thus enable learners to understand the knowledge of computer motherboard architecture. Therefore, learners' use of MARLS are expected to lead to favorable learning outcomes. Although MARLS mainly convey basic concepts, the learning content and materials delivered through them may be inherently complex. MARLS with 3D graphics are appropriate for instructors or learners to conveniently understand sophisticated knowledge and develop specific expertise. Therefore, evaluating the success of MARLS is highly dependent on learners' continued intention to use MARLS and their perceived learning effectiveness. However, technologically enhanced learning (i.e., AR-based learning) is not always effective in terms of delivering knowledge to learners from the perspectives of information feedback and flow theory in different learning contexts (Cruz & Uresti, 2017; Guo & Ro, 2008). There is still a lot of ambiguity (e.g., interactive mode and degree of fidelity) in the findings of prior studies regarding the usefulness of MARLS, and there is a need for more studies on such applications (Maier et al., 2016, Jiu et al, 2022; Skulmowski et al., 2022). Based on the literature review, the flow theory and cognitive load theory can help us disclose hidden information related to learners' learning experience, including the improvement of their logical reasoning skills, the utilization of their cognitive resources, and the impact of information overload on the learners' learning effectiveness (e.g., Chang et al., 2017; Hohnemann et al., 2022; Sun et al., 2019; Tang et al., 2022). In addition, the quality of information feedback and flow experience is essential in ensuring good understanding eventuates. This formative assessment can help stakeholders deeply understand and connect the requirements of users in the teaching/learning process (Tu & Chu, 2020).

Chang et al. (2017) argue that integrating an AR learning environment into the learning material or context elements can add diversity of experience and knowledge and enrich the learning material. In the learning process, the learner's perceived challenge of MARLS is a determining factor: the more fantastic the flow experience of the challenge, the greater the perceived learning effectiveness. The flow experience facilitates positive and pleasant psychological elements or emotional states, which are crucial in helping students adjust their behavior and achieve effective learning (Tang et al., 2022). Additionally, adequate instructional design can reduce the formation of the extraneous cognitive load of learners, which tends to unnecessarily consume the learners' cognitive resources (Sweller et al., 1998). Thus, this study evaluated the MARLS to practice the basic concepts of computer motherboard architecture. MARLS offer a novel and 3D learning space through visual and tactile interaction with the learning materials to enhance learner flow experiences. In this study, task-oriented learning materials could be accessible via the navigation hyperlinks, and the MARLS structure is thus based on the AR application. MARLS can provide dynamic visual and tactile guidance by information feedback to aid learners' understanding and higher-order thinking in achieving predictable perceived learning effectiveness (Chiang et al., 2022; Ebadi & Ashrafabadi, 2022). Nevertheless, studies that evaluate the effectiveness of the use of MARLS for supporting student learning in higher educational contexts by adopting a comprehensive perspective that incorporate the concepts of information feedback, flow experience, and cognitive load theory are missing from the existing literature.

Therefore, this study aims to fill this gap by focusing on investigating the effectiveness of the use of the MARLS that are developed to help students learn via mobile devices (i.e., smart phones, tablets, or other mobile computing devices). To be specific, the investigation of this study is rooted in the interaction between MARLS, learning materials, and the learner. Such interaction determines learners' perception of whether the MARLS are an effective learning tool. Consequently, we propose that the learning content and environment can achieve a good integration to enhance the learning process and increase the benefits of using MARLS in higher education settings. Therefore, our research questions (RQs) are as follows:

RQ: 1) Does information feedback of MARLS significantly influence learners' flow experience, perceived learning effectiveness, and continued intention to use MARLS?
2) Does the extraneous cognitive load significantly moderate the relationship between information feedback and perceived learning effectiveness?

To answer those two primary research questions, this study developed the MARLS using the AR-based technologies to assist college students in learning important knowledge related to the computer hardware architecture. A total of 204 students that were recruited from ten universities and had no experience in learning the subjects covered by the MARLS of this study served as the research participants. Those students were asked to take a pre-test first, and then to use the MARLS. After completing the learning processes of the MARLS, they were asked to take a post-test and then fill out a survey in order to offering sufficient and valid data that could be used to evaluate their perception regarding the MARLS and their learning effectiveness. Details of the research design, including the sampling method, specification of the MARLS, and the data collection procedures, are presented in the subsequent sections.

2 Literature review and hypotheses development

2.1 Information feedback

Information feedback is critical to smooth task learning and perceiving a sense of interaction in the knowledge acquisition process when learners use MARLS (Burns et al., 2021; Fang, 2020). MARLS are specific instruction-based learning systems that offer knowledge-related information to learners. Thus, the information feedback of learning materials from MARLS regarding computer motherboard architecture is reliable, stable, and makes sense. MARLS may assist learners in evaluating their flow experience or observing extraneous cognitive load when they obtain high-quality information feedback (Zou et al., 2021). As mentioned above, the intervention of extraneous cognitive load on the effects of information feedback on learning-related outcome variables is an under-addressed issue in the MARLS literature.

Some studies indicated that AR-based applications could provide learners with various types of real-time information feedback, including visual and haptic feedback, in order to enhance their learning effectiveness (Belda-Medina & Calvo-Ferrer, 2022; Chiang et al., 2022; Jaszczur-Nowicki et al., 2021; Rodríguez et al., 2022; Wang et al., 2022; Yilmaz et al., 2022). Such timely and interactive feedback can help students better understand their learning goals, enhance their concentration and learning motivation, and arouse their interest or curiosity (Steele & Fullagar, 2009; Windasari & Lin, 2021).

However, AR-based learning may differ from other educational contexts, and different findings regarding the effects of information feedback on learning performance in other educational contexts have been reported in the literature. For example, some studies of other educational contexts found that the feedforward and outcome feedback offered by teachers are insignificantly related to students' learning effectiveness (Burns et al., 2021; Lerch & Harter, 2001). Additionally, students' competence did not significantly improve in the VR-supported project when they receive unfavorable cognitive feedback from their peers (Lin & Wang, 2021). Moreover, Karelaia & Hogarth (2008) found that cognitive and outcome feedback did not help for learning (i.e., judgmental consistency). Finally, information feedback did not affect flow experience in the context of learning about business simulation systems (Yen & Lin, 2020).

Based on the discussion above, the effects of information feedback on students' learning effectiveness vary across different educational contexts. Thus, we can infer that more studies of information feedback are needed to better understand its impact on learning outcome in the MARLS context, because the effects of information feedback are dependent on the features of learning tasks, the design of learning materials and processes, and the tools or technologies used to support learning.

Additionally, AR-based applications offer individualized information feedback regarding students' learning progress to the instructors, which can thus assist the instructors to identify the students' misperceptions of learning materials or learning difficulties (Ng, 2022; Nikou et al., 2022). Information feedback of MARLS can overcome these obstacles, including videos demonstrating the multimedia learning materials and correct operations regarding the concepts of the computer motherboard architecture that help learners to engage in a personalized learning process. The procedures may reduce misunderstanding or enable them to learn at their own pace. In other words, MARLS provide personalized learning feedback to learners, giving them more opportunities to improve their knowledge acquisition and guide learning.

2.2 Flow theory

The flow experience is a significant issue in the context of higher education in terms of examining the learning outcomes of various educational activities (Buil et al., 2019; Yen & Lin, 2020), game-based learning (Hsieh et al., 2016; Li et al., 2021), and continued intention (Goh & Yang, 2021). Csíkszentmihályi (1975) proposed the fundamental concept of flow and explained how individuals feel highly focused attention, a sense of control, and enjoyment of work or during activities (i.e., learning, games, sports, adventure recreation, etc.). Based on flow theory, individuals who experience flow states at work or during activities can be nervous and concentrate on what they do in a unique context. Some researchers further indicated that if the presentation of learning content/material matches learners' needs, the learning goals can be achieved by consuming less efforts, which can lead to high levels of the learners' feeling of a sense of control, satisfaction regarding the learning process, and subsequent learning motivation (Cheng, 2017; Koç et al., 2022; Okai-Ugbaje et al., 2022). Additionally, the timely feedback may benefit learners by keeping them focused, increasing their interest or enjoyment in the knowledge acquisition process, thus inducing higher-order thinking or learning effectiveness (Chiang et al., 2014; Ebadi & Ashrafabadi, 2022; Lin & Chen, 2020; Mystakidis et al., 2022; Wu, 2019). This is because individuals can perceive a sense of control exceeding their experiences. In summary, it can be inferred that individual flow experience plays an important mediating role in the relationship between information feedback and learning effectiveness, which is rarely examined in educational settings in which mobile AR applications are applied. Therefore, this study, by using an experimental research design, intends to specifically address this research gap in the literature.

In this study, the flow experience is considered to be composed of three main categories (Goh & Yang, 2021). First, *focused attention* refers to the degree to which individuals immerse and concentrate their attention on the visual screen and execute an action by forgetting everything around them. Second, a *sense of control* refers to an individual's control exceeding activity requirements without conscious effort. Third, *enjoyment* refers to how individuals assess a particular feeling of well-being due to cognitive and affective evaluations of a specific activity. We propose the three elements of a flow state can be applied to learning activities through the learning content of MARLS because learners' flow state of MARLS during the learning process is positively associated with their perceived learning effectiveness and continued intention (AlNajdi et al., 2020; Ibáñez et al., 2014).

2.3 Cognitive load theory

Cognitive load theory is one of the famous theoretical perspectives that concerns the relationship between cognition and educational instructions in educational psychology (e.g., Cheng, 2017; Leppink-Heuvel & van den Heuvel, 2015; Liao et al., 2019; Paas et al., 2003; Skulmowski & Xu, 2022). It has been adopted in research dealing with the design of multimedia learning materials. Learning is tending conscious; thus, the learning process is complicated and full of effort (Sweller, 1994). This learning process may be considered cognitive. Similarly, it heavily relies on a limited amount of working memory and relevant data from vast amounts of information in the long-term memory. Learners' possession of critical knowledge and information feedback in advance (i.e., the form of information presented in 3D) can decrease their extraneous cognitive load in learning contexts (Lai et al., 2019; Moreno & Mayer, 2007; Sweller et al., 1998). Thus, for video-based social media platforms (e.g., MARLS), the visual content that delivers the learning materials must match the tactile operations of the learners to decrease their cognitive load. Additionally, the learning task complexity relates to individuals' previous knowledge constituting their cognitive load (Sweller, 1994). The use of an inappropriate instructional method for teaching or learning may increase the extraneous cognitive load of learners. In this study, MARLS were considered a learning system that integrates learning materials and the virtual environment and links what individuals learn in real-world settings to their prior knowledge. The provision of adequate information feedback to learners in MARLS-supported educational contexts can strengthen learners' concentration, cognition, and reflective processes.

2.4 Hypothesis development

Based on the information feedback, flow, and cognitive load theories, this study proposes the learners' psychological states of continued intention to use MARLS and perceived learning effectiveness are influenced by their flow experience and information feedback in technology-enhanced learning. Following the fundamental

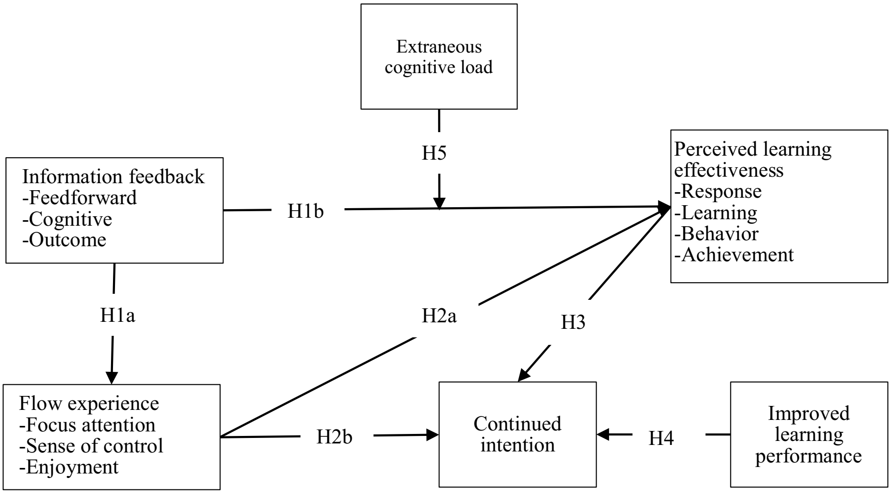

Fig. 1 Conceptual research model

notion of flow theory, this study considers the MARLS attributes of information feedback, visual and tactile information, and learning content as evaluation criteria among learners to examine the variables as aforementioned (Fig. 1).

Feedback is a resource (Bakker, 2005). The potential learning experience is weakened if the learner does not receive clear goals or explicit information regarding completion, the amount, or timing of the content (Maier et al., 2016). Researchers indicated immediate feedback (i.e., feedforward) is one of the preconditions of the flow state (e.g., Buil et al., 2018, 2019). Useful information feedback is a required component of favorable flow experience derived from individual tasks (Csíkszentmihályi, 1990). Steele and Fullagar (2009) found a significant relationship between performance feedback and flow exists when students engage in various academic activities. Therefore, some challenges and skills are necessary for tasks or activities, resulting in an optimal learning experience in a virtual learning environment. Similarly, information feedback (i.e., feedforward, cognitive, outcome) is meaningful and valuable for learners, improving their flow state (i.e., concentration, a sense of control, and enjoyment) (Csíkszentmihályi, 1975, 1990; Hattie & Timperley, 2007; Windasari & Lin, 2021). It can be inferred feedback is positively related to flow experience (e.g., Buil et al., 2018; Guo & Ro, 2008; Kajitani et al., 2020; Wang & Wang, 2008). Accordingly, the hypothesis is as follows.

H1a. Information feedback is positively associated with the flow experience.

In the virtual learning context, visual or tactile advanced learning technologies can assist students to enhance immersion and engagement (e.g., Ibáñez et al., 2014; Petersen et al., 2022; Shin, 2019). This can facilitate their engagement in and enhance their concentration on the learning tasks. Therefore, learners with experiencing a high level of flow state were more likely to identify or develop feasible solutions for problem-solving (Liu et al., 2011; Yang et al., 2019). Additionally, learners are likely to immerse themselves in learning tasks facing challenges when they achieve a flow state, thus, exhibiting better learning achievement (Hsieh et al., 2016; Sun et al., 2017; Wang & Hsu, 2014). The positive information feedback (i.e., audio-visual effects) may strengthen their confidence in obtaining future achievements (Teng, 2018). Some studies reported accurate responses or assessment feedback can significantly affect learners' academic performance (Connolly et al., 2012; Zhao et al., 2021). Specifically, MARLS are an interactive teaching system that can provide immediate feedback and guidance for learners, influencing their cognitive processing (Müller & Wulf, 2022), behavioral engagement (Sun et al., 2019), and learning performance or perceived learning effectiveness (Alexiou et al., 2020; Eckes & Wilde, 2019; Yen & Lin, 2020). Accordingly, the hypothesis is as follows.

H1b. Information feedback is positively associated with perceived learning effectiveness.

Previous studies reported the flow experience positively affects perceived learning effectiveness in a computer-based instructional environment (e.g., Ebadi & Ashrafabadi, 2022; Wang & Hsu, 2014; Yen & Lin, 2020). For example, Rachmatullah et al. (2021) found a game-based environment promotes students' flow experiences of genetics learning and thus positively influences their posttest scores. Li et al. (2021) reported enjoyment leads to optimal learning, and thus positively impact learners' perceived learning effectiveness (Alexiou et al., 2020). Therefore, it can be considered the flow experience can appraise the benefits in a virtual learning environment. Accordingly, the hypothesis is as follows.

H2a. Flow experience is positively associated with perceived learning effectiveness.

In traditional instruction, learners typically must spend a lot of time and physical energy to engage in the learning content or skills. Nowadays, technology-enhanced applications give learners immediate access to learning materials. In a specific learning system, learners have less at risk when they engage in their learning tasks. In such a case, they will be more likely to browse and collect information for their learning. In this study, MARLS provide learners with an opportunity to learn and apply AR applications for obtaining focused attention, a sense of control, and pleasure. Thus, researchers may need to consider the aspects of flow experience and continued intention. This may be why learners' willingness to continue using MARLS to improve their academic performance needs to examine their decision-making behaviors. Several studies indicated learners perceived flow experience while using a learning system or service affects their continued intention (e.g., Choi, 2022; Goh & Yang, 2021; Tuncer, 2021; Yang et al., 2014). When learners are in an optimum emotional state of the learning experience, they will have concentration, a sense of control, and enjoyment, influencing their continued intention to use MARLS (Zha et al., 2016). Accordingly, the hypothesis is as follows.

H2b. Flow experience is positively associated with the learner's continued intention to use MARLS.

Currently, online learning has spread widely to various levels of learners. However, continuing to use technology-enhanced systems is still a critical issue (e.g., Liao et al., 2015; Lin et al., 2014; Wang & Lin, 2021). This study considers the actual success of MARLS to be related to learners' continued usage behaviors that can assist learners' perceptions and improve their perceived learning effectiveness. They will be willing to use MARLS to support their learning and enhance their effectiveness. Previous studies on the continued intention to use online learning systems suggest perceived learning effectiveness significantly affects learners' behavioral intention (Liaw & Huang, 2016; Liu et al., 2021; Tawafak et al., 2020). In this study, the purpose of MARLS is to facilitate learners' learning of the knowledge of the computer motherboard architecture, making them feel confident to engage in learning tasks and subsequent assessments, thus promoting their intention to continue using MARLS. It can be inferred perceived learning effectiveness is associated with learners' intention to continue using the MARLS. Accordingly, the hypothesis is as follows.

H3. Learners' perceived learning effectiveness is positively associated with their continued intention to use MARLS.

The impact of AR technology has widely influenced learners' behavioral patterns in education settings. For example, some prior studies argue a guide/guideless video or game can significantly affect a learner's academic performance in a learning activity (e.g., Lai et al., 2019; Tawafak et al., 2020). Therefore, the design of learning technologies may involve a variety of information feedback to meet the users' learning goals and desired academic performance success. Research has shown these technologies aim to achieve faster information feedback and flexibility for learners; similarly, they have to take on challenging learning tasks in their learning process (Wang & Lin, 2021). Previous studies argued learners' learning performance/outcome is associated with their continued intention (Wongwatkit et al., 2020). Accordingly, the hypothesis is as follows.

H4. Learners' improved learning performance is positively associated with their continued intention to use MARLS.

Previous research indicated extraneous cognitive load is negatively associated with academic performance or the effectiveness of cognitive processes (Cheng et al., 2021; Su, 2016). However, a study stated proper task demands or characteristics in a learning procedure or instructional design could alter the extraneous cognitive load of learners (Skulmowski & Rey, 2017). In this study, the learning material is not pure text-based which may generate additional cognitive load for most participants. Additionally, most of them are using MARLS for the first time in their learning tasks at a high level of thinking about the new information, and thus, the impact of extraneous cognitive load cannot be neglected (Hollender et al., 2010; Jiang et al., 2018). They need to integrate the visual and tactile sensations and follow the given information from MARLS, which may influence their cognitive load (Makransky et al., 2019; Petersen et al., 2022). Lee and Hong (2022) found cognitive load has a moderating effect on the relationship between epistemic prompting and students' multimodal multiple text comprehension. Accordingly, the hypothesis is as follows.

H5. Extraneous cognitive load negatively moderates the relationship between information feedback and perceived learning effectiveness.

3 Methodology

3.1 Experiment

The experiment conducted for this study aimed to understand the impact of MARLS in learning the knowledge of computer motherboard architecture. In this study, information feedback and flow experience were examined to discover their effects on perceived learning effectiveness and to understand their continued intention on learners' improved learning performance in the contexts of using MARLS. The design of the MARLS developed for this study was described in the subsequent sections.

The MARLS used in this study were developed to help student learn about the technical specifications of the motherboard of a personal computer and the key components of the motherboard, which is one of the learning subjects of the course of "Computer Architecture." The research participants were able to use the MARLS using a mobile device running on the Android operating system, including smart phones and tablet computers. To avoid the potential disturbance in the surrounding environment, the research participants of this study were asked to complete the learning processes of the MARLS using a tablet computer in a lab designated by the researchers. The research participants were asked to take a pre-test and a post-test before and after using the MARLS in order to offer us sufficient data to evaluate how well their knowledge of the focal learning subjects was improved. After completing the learning processes of the MARLS, they were also asked to fill out a survey in order to offering data that could be used to evaluate their perception regarding the MARLS and their perceived learning effectiveness.

Before using the MARLS, the designed system would give the learners five questions to evaluate their prior knowledge regarding computer motherboard architecture (i.e., the pre-test). The feedback included three parts. First, regarding feedforward, MARLS presented some instructions to learners regarding how to operate and control the MARLS functions as well as the learning objectives of the MARLS. Then, the learner could begin the learning tasks and read the learning materials via the MARLS interface to gain new knowledge. The research participants could immerse themselves in the learning content through the guidance of the feedforward that included information for helping them understand the relevant concepts of computer motherboard architecture. Second, after completing all learning content, the system showed a number of exam questions to assess the levels of the students' learning effectiveness (i.e., the post-test). Third, MARLS automatically provided students with different cognitive feedback and outcome feedback based on the learners' post-test scores. The former provided the relevant instructions for the post-test response, while the latter provided learners with post-test scores. To be specific, when a participant's post-test score was 100 of out 100, the MARLS provided a message to the participant to indicate that they had understood the learning materials very well. Additionally, MARLS offered instructions (i.e., cognitive feedback) to a participant by referring to the exam questions that the participant got the answers to wrong in order to help him/her improve his/her understanding of the focal learning materials when his/her post-test scores were between 60 and 99. Finally, MARLS provided a participant who scored lower than 60 in the post-test with instructions (i.e., cognitive feedback) related to the exam questions that he/she got the answers to wrong in order to help him/her improve his/her understanding of the focal learning materials, and then asked him/her to take the post-test again (see Fig. 2). While the MARLS were designed to repeat the same process of retaking the post-test until the post-test score of a participant was 60 or above out of 100 (since the score of 60 out of 100 is the minimum score required to pass an exam in Taiwan), none of our participants was required to take the post-test for more than two times.

3.2 System overview of the MARLS used

The MARLS included three major components: (1) interactive interfaces that include fingertip videos, interactive visual functions, and information rendering overlay; (2) hardware components that include camera, interactive semantics, and interactive data for introducing the hardware components (i.e., mainframe computer motherboard architecture, central processing unit, and random access memory (RAM)); (3) communication tools that include a fingertip interactive information acquisition module and an online registration function for the authentication of user identities (Jiu et al., 2022; Westerfield et al., 2015). In other words, the critical elements of the MARLS designed for this study include integrated real-world and virtual content using 3D AR-based technology and functions of real-time interaction (Belda-Medina & Calvo-Ferrer, 2022). The participants can use their fingertips as a virtual pen to get more information or knowledge feedback from the MARLS. Several researchers found that using 3D AR-based learning applications can enhance students' learning effectiveness by enabling students to acquire enhanced visuospatial perception that can help them better understand the learning materials, and thus result in better flow experiences in terms of enhanced cognitive skills, enjoyment, interest, and engagement (e.g., Belda-Medina & Calvo-Ferrer, 2022; Koç et al., 2022; Demitriadou et al., 2020; Mystakidis et al., 2022). The reason is that when students perceive the learning processes are under their control and do not beyond their cognitive abilities because of the provision of appropriate and timely information feedback, they are likely to be interested and concentrated in the focal learning tasks and perceive their learning experience to be enjoyable.

In this study, the participants can perform their learning tasks through 3D models and interactive omnidirectional videos that may increase their learning motivation and keep their cognitive resources available for learning (Skulmowski & Xu,

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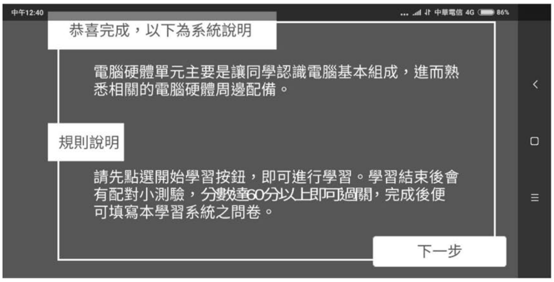
<td>
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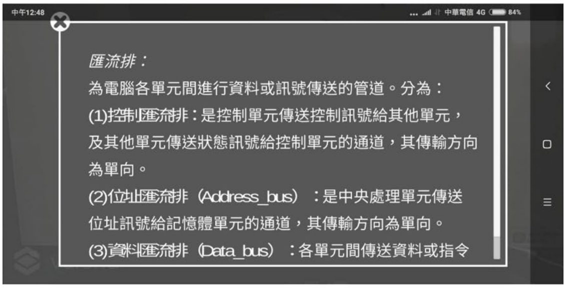
<td>
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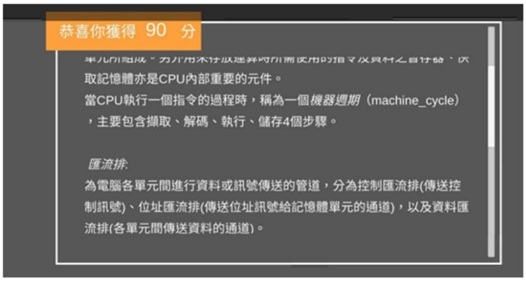
<td>
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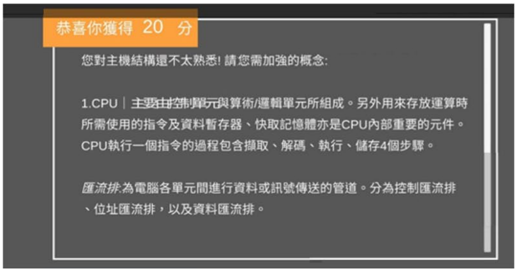
<td>
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<td>If the score is less than 60 points, asking the learner to think more in detail about the concept.</td>
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Fig. 2 The learning procedures

2022). A worth noting advantage of 3D-based learning functions, although they are more challenging for the human brains to process, is that they can overcome the disadvantages of the learning processes supported by two-dimensional (a flat object) visual presentation, such less effective and less interesting human–computer interactions and poor virtual control ability regarding the interactive assembly instructions (Alhonkoski et al., 2021; Jiu et al., 2022). Additionally, the main learning processes of the MARLS were performed by providing the learners with feedforward feedbacks for reducing unnecessary cognitive efforts devoted prior to the actual learning processes, and with cognitive feedbacks for enhancing learners' odds of acquiring the accurate knowledge via a smart mobile device.

Additionally, the research participants followed the instructions given by the MARLS to complete the learning tasks by performing fingertip movement via a tablet computer running on the Android operating system (Fig. 3). Such conditions can enable the participants to focus on the learning tasks for acquiring the knowledge related to physical objects, such as computer hardware, more easily and provide them with a sense of control and enjoyment. Therefore, the design of the MARLS of this study may facilitate learners' critical/analytical thinking, particularly in the process of learning sophisticated knowledge. Additionally, the design of the MARLS used allowed the research participants to use the smart mobile device to freely observe the pictures of the components of a motherboard using different angles, which could increase the learners' perceived level of quality of interacting with the virtual learning content of the MARLS, and thus enhance the immersion effects on the learners and produce a better flow experience for the learners. The learning content and information feedback were immediately demonstrated through dialogues or guidance. The key concepts of the focal learning topic was incorporated into both the MARLS learning instructions (i.e., feedforward and cognitive feedback) and the exam questions in an interactive and more interesting manner to motivate participants to use the MARLS to achieve their learning goals. In other words, the MARLS enable learners to learn in a comfortable and enjoyable environment by performing the AR-supported interactive learning processes using mobile devices. Moreover, the feature of ubiquity of the MARLS, similar to that of many different mobile applications, makes it possible for learners to learn anytime and anywhere based on an informal curriculum and a flexible schedule and to learn the knowledge that they need more thoroughly by repeatedly performing those learning processes of the MARLS as many times as they want.

3.3 Data collection

This study aims to examine the effects of information feedback on flow experience, perceived learning effectiveness, and learners' continued intention regarding using the MARLS for their learning tasks. Ethics approval for this study was obtained from the University Governance Framework for Human Research Ethics of the authors' institute approved (HREC-109–088-2). Additionally, all participants were informed of the research purposes and volunteered to participate in the survey, treating their information as confidential.

This study uses a psychometric survey to examine the proposed research model and hypotheses. By distributing the information of the experiment of this study through the online student forums of ten randomly selected universities in Taiwan,

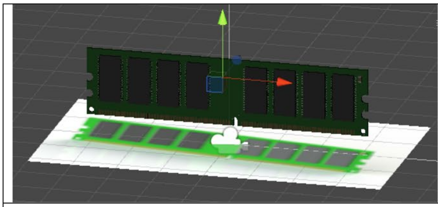
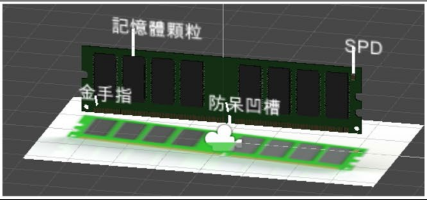
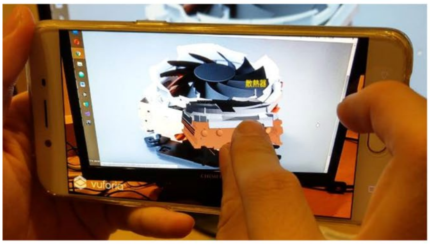
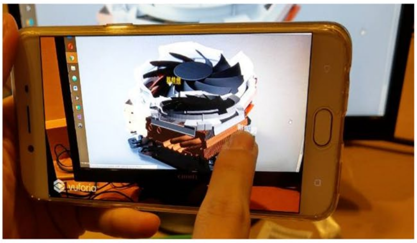
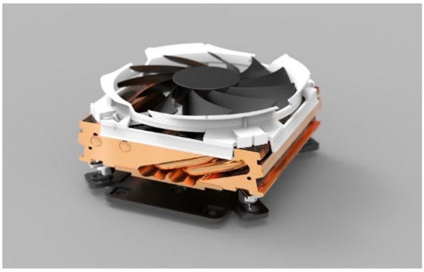
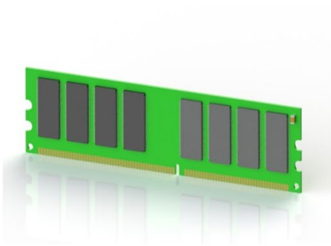
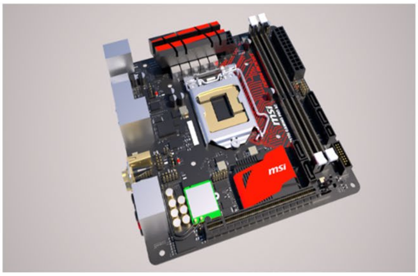
	
Importing Unity SDK into the system, importing recognized images and models, and setting parameters.	Adding the text labels to the model, setting the text-based instructions that appear when the participants click the text label.
	
The participant uses a two-finger gesture to zoom out the screen of the model.	The participant rotates the model to the right.
	
Central processing unit.	Memory model diagram (RAM).
	
Motherboard model diagram.	The 3D model diagram of a motherboard is presented on a tablet.

Fig. 3 The MARLS design

the authors recruited 204 students from those universities who had no experience with MARLS or no experience in taking courses related to computer hardware architecture to ensure there were no significant differences in the respondents' prior knowledge regarding the use of the system or the learning subjects. All participants were asked to finish a pre-test exam and fill out a survey immediately to examine their prior knowledge. Each qualified participant was asked to download the MARLS application using their tablet or mobile when it was convenient to participate in this experiment. Additionally, the participation in the experiment of this study was totally voluntary to the potential participants, and none of the authors have any conflicts of interest or noticeable relationships with the 204 participants.

No interaction or conversations were allowed; each participant had to independently complete the subjects' learning process during the experiment to avoid affecting the results. Moreover, they were asked to finish a post-test exam and fill out the questionnaire when they completed their learning tasks. Each participant received a coupon of around USD 3.5 as a gift for their voluntary participation in the experiment of this study. Finally, a total of 204 valid responses were analyzed to validate the proposed hypotheses. The demographic details showed male participants comprised 107 (52.45%), 202 (99.02%) participants were in the age group of 20–25 years, 94 (46.08%) had a bachelor's degree, and 104 (50.98%) had a master's degree or above.

3.4 Instrument

The constructs of information feedback, flow experience, perceived learning effectiveness, continued intention, and improved learning performance were measured using multi-item scales (see Appendix Table 3). The operationalization variables are as follows.

Information feedback was measured by nine items (three items each for feedforward, cognitive feedback, and outcome feedback) whose wordings were modified to fit with the research context of this study (Brooks et al., 2019; Faber et al., 2017; Hattie & Timperley, 2007; Maier et al., 2016). Flow experience was evaluated by nine items (three items each for focused attention, sense of control, and enjoyment), slightly edited by an adapted version of the studies (Ahn et al., 2007; Buil et al., 2019; Rodríguez-Ardura & Meseguer-Artola, 2017). These items of *flow experience* are also studied in the context of computer-based learning/instruction (Ibáñez et al., 2014; Li et al., 2021; Wang & Hsu, 2014). Moreover, a total of twelve items were adopted to assess *perceived learning effectiveness* to examine students' response (three-item), learning (three-item), behavior (three-item), and achievement (three-item). The aforementioned items were employed and modified from Chrysafiadi and Virvou (2013) and Huang et al. (2015). Three items measured extraneous cognitive load employed by Leppink-Heuvel and van den Heuvel (2015). *Continued intention* was evaluated by three items that modified the version of Mohammadyari and Singh (2015). A seven-point scale ranging from 1 ("strongly disagree") to 7 ("strongly agree") scored all items. Additionally, the *improved learning performance* was measured by the normalized scores of the post-test and pre-test of the research participants.

Additionally, a pilot test was conducted to evaluate the reliability of the survey items adopted. A total of thirty participants were invited to participate in the pilot test, and the data collected was assessed by checking the Cronbach's alpha coefficients of the first-order latent constructs. The results indicated the Cronbach's alpha coefficients of all the first-order latent constructs were greater than the recommended threshold value of 0.7 (ranging from 0.71 to 0.89), indicating the survey items of all the constructs had acceptable levels of reliability. All items were thus used in the subsequent data collection procedure.

3.5 Data analysis method

The proposed research model performed a confirmative factor analysis by Smart PLS 3.0 to assess these scales' psychometric properties in terms of adequacy, including reliability, convergent, and discriminant validities. By using the partial least square structured equation modeling (PLS-SEM) approach, this study examines the validity and reliability of the data collected, and then validates the developed research hypotheses. Additionally, PLS-SEM can thoroughly explain the content validity using its latent indicators of the second-order formative construct. Therefore, the proposed hypotheses were tested through a bootstrapping procedure with resampling at 5,000 times and a 95% confidence interval.

4 Results and discussion

4.1 Hypothesis testing results and discussion

All the proposed hypotheses were supported (Fig. 4). The information feedback is positively and significantly associated with flow experience (H1a: $\beta = 0.39$, $t = 6.54$) and perceived learning effectiveness (H1b: $\beta = 0.48$, $t = 10.23$). There was a positive and significant relationship between flow experience and perceived learning effectiveness (H2a: $\beta = 0.30$, $t = 5.58$), and continued intention (H2b: $\beta = 0.22$, $t = 3.14$), respectively. Perceived learning effectiveness is positively and significantly associated with continued intention (H3: $\beta = 0.56$, $t = 8.95$. Improved learning performance is positively and significantly associated with continued intention (H4: $\beta = 0.13$, $t = 2.32$). Extraneous cognitive load negatively and significantly moderated the relationship between information feedback and perceived learning effectiveness (H5: $\beta = -0.14$, $t = 2.51$).

In examining H1a, the finding indicated information feedback is positively related to perceived learning effectiveness, consistent with the previous studies (Buil et al., 2018; Guo & Ro, 2008; Kajitani et al., 2020; Wang & Wang, 2008). This suggests learners with more information feedback will reduce the uncertainty of the learning requirements and increase the strength of belief in the learning environment of MARLS. Particularly in this study, relative information feedback may make them engage in and do their best; thus, potentially improving their incentive

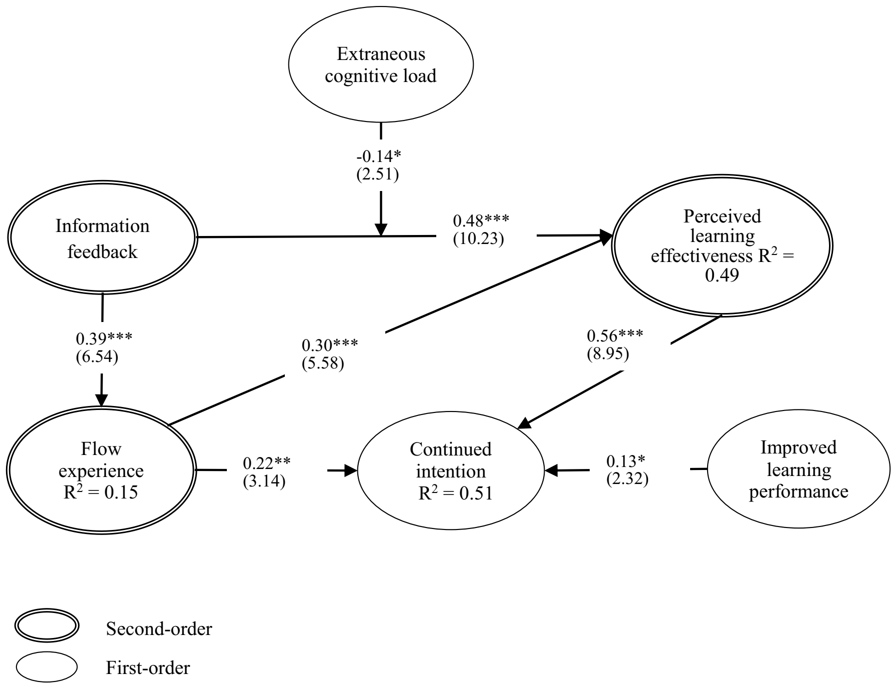


Fig. 4 Results of hypotheses testing of the research model. Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

to study and leading to better-perceived learning effectiveness. Similarly, the result of H2a reveals a learner with a higher flow experience is associated with perceived learning effectiveness, which is in line with previous studies (e.g., Ebadi & Ashrafabadi, 2022; Li et al., 2021; Wang & Hsu, 2014; Yen & Lin, 2020). This study suggests MARLS can enhance learners' flow experience (i.e., focused attention, sense of control, and enjoyment), resulting in better-perceived learning effectiveness.

In examining H1b, the findings indicated information feedback is positively associated with flow experience, consistent with the findings of previous studies (e.g., Alexiou et al., 2020; Alexiou et al., 2020; Eckes & Wilde, 2019; Yen & Lin, 2020). Real-time or detailed information feedback may facilitate the flow experience in the MARLS context while promoting focused attention, a sense of control, and fun in MARLS learning practices.

In examining H2b and H3, the results revealed learners with a high level of flow experiences would have a higher level of continuance intention to use MARLS for their learning. H2b is consistent with previous studies (e.g., Choi, 2022; Goh & Yang, 2021; Tuncer, 2021; Yang et al., 2014) and H3 is in line with previous studies (e.g., Liaw & Huang, 2016; Liu et al., 2021; Tawafak et al., 2020). Flow experience is mainly derived from focused attention, a sense of control, and enjoyment to maintain or build high levels of positive psychological state in a learning activity. Thus, learners with a higher flow experience will promote their continuance intention positively. In the case of visual- and tactile-based learning, enjoyment and continuance intention are associated with each other. Additionally, MARLS reveal it can enable and support learner tasks, leading to a strong continued intention to use MARLS.

The confirmation of H4 is in line with the result of Wongwatkit et al. (2020). This means MARLS can assist learners to improve learning performance, leading to the development of a high willingness to use this learning system.

H5 is a novel finding that can provide a reference opportunity to improve the teaching/learning design. H5 reveals extraneous cognitive load significantly and negatively moderates the influences of information feedback on perceived learning effectiveness. Additionally, extraneous cognitive load is significantly negatively related to perceived learning effectiveness (β=-0.12, t=2.55), consistent with a previous study (Chang, 2018). This study suggests the MARLS developers and course instructors need to carefully design the mechanisms for offering information feedback in the MARLS use context (i.e., learning materials and teaching practices) to diminish learners' cognitive load (Ebadi & Ashrafabadi, 2022; Moreno & Mayer, 2007). Offering more ongoing feedback for instructions, clear visual presentations, and rearranging the sequence/range of examples might help them to improve their perceived learning effectiveness.

Overall, the findings of this study have pointed out the important influences of information feedback on perceived learning effectiveness by enhancing the flow experience of MARLS users. Therefore, pedagogical methods that are supported by MARLS may offer timely and adequate information feedback to students in order to arouse their interest toward learning tasks, which will lead to more favorable flow experience and better learning outcomes of the students.

4.2 The validity of measurement model

First, in the measurement model, convergent validity primarily examines the proposed constructs that are well reflected by its measured items, consisting of the factor loadings, internal consistency reliability, composite reliability (CR), and average variance extracted (AVE) (Fornell & Larcker, 1981). As shown in Appendix Table 3, the values of factor loadings show all items were significantly greater than 0.7. Table 1 shows the Cronbach's alpha values ranged from 0.7 to 0.89, the CR values ranged from 0.83 to 0.93, and the AVE ranged from 0.62 to 0.81, exceeding the criteria of 0.7, 0.7, and 0.5, respectively (Hair et al., 2019). The results revealed all constructs with excellent reliability and convergent validity were obtained in this study.

Additionally, discriminant validity evaluates the structural model and whether the survey constructs are empirically distinct from other constructs (Hair et al., 2019). According to the criteria (Fornell & Larcker, 1981), the AVE value of each construct should be larger than the squared inter-construct correlation coefficients between the others in the research model; similarly, no AVE value is less than 0.50. Table 1 shows the AVE of each construct was larger than the squared inter-construct correlation coefficients between each construct.

Further, Henseler et al. (2015) stated the correlations' Heterotrait-Monotrait (HTMT) ratio could be used to assess the discriminant validity of the measurement model. High HTMT values in the research model reveal the discriminant validity is debatable. They suggest the HTMT values did not exceed 0.90 for structural models with constructs, and thus, the conceptual meaning of these

Table 1 The results of discriminant validity

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Feedforward	**0.68**												
2.Cognitive	0.15 (0.5)	**0.69**											
3.Outcome	0.20 (0.57)	0.4 (0.79)	**0.72**										
4.Focus attention	0.09 (0.38)	0.13 (0.46)	0.05 (0.28)	**0.75**									
5.Sense of control	0.04 (0.25)	0.04 (0.29)	0.03 (0.23)	0.16 (0.5)	**0.62**								
6.Enjoyment	0.07 (0.33)	0.06 (0.3)	0.01 (0.16)	0.19 (0.52)	0.07 (0.32)	**0.77**							
7.Response	0.21 (0.64)	0.3 (0.75)	0.18 (0.56)	0.23 (0.63)	0.06 (0.33)	0.15 (0.5)	**0.63**						
8. Learning	0.19 (0.56)	0.27 (0.65)	0.13 (0.43)	0.05 (0.28)	0.02 (0.17)	0.11 (0.4)	0.4 (0.83)	**0.72**					
9. Behavior	0.11 (0.43)	0.14 (0.47)	0.07 (0.33)	0.11 (0.41)	0.07 (0.34)	0.18 (0.51)	0.37 (0.81)	0.39 (0.78)	**0.70**				
10. Achievement	0.19 (0.53)	0.26 (0.62)	0.2 (0.54)	0.12 (0.41)	0.08 (0.35)	0.13 (0.41)	0.46 (0.86)	0.44 (0.78)	0.56 (0.89)	**0.81**			
11. Extraneous cognitive load	0.04 (0.24)	0.03 (0.21)	0.04 (0.24)	0 (0.09)	0 (0.1)	0 (0.06)	0.03 (0.25)	0.08 (0.35)	0.01 (0.15)	0.05 (0.26)	**0.72**		
12.Continued intention	0.07 (0.35)	0.14 (0.49)	0.06 (0.33)	0.19 (0.54)	0.12 (0.46)	0.13 (0.44)	0.32 (0.76)	0.27 (0.65)	0.34 (0.74)	0.4 (0.76)	0.01 (0.14)	**0.71**	
13Improved learning performance	0 (0.11)	0.01 (0.12)	0.02 (0.18)	0 (0.07)	0 (0.06)	0.02 (0.14)	0.01 (0.14)	0 (0.11)	0 (0.06)	0 (0.08)	0 (0.02)	0.02 (0.17)	**1**

Table 1 (continued)

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13
Mean	5.54	5.82	5.29	5.38	5.09	5.08	5.46	5.86	5.56	5.66	3.13	5.69	1
SD	0.95	0.91	1.15	0.98	0.86	0.98	0.83	0.79	0.88	0.85	1.28	0.94	-
Composite reliability	0.86	0.87	0.89	0.9	0.83	0.91	0.84	0.89	0.87	0.93	0.89	0.88	1
Cronbach's alpha	0.76	0.77	0.8	0.83	0.7	0.85	0.71	0.81	0.78	0.89	0.8	0.79	1

N = 204; SD = standard deviation; Heterotrait-Monotrait (HTMT) ratios are in parentheses; the average variance extracted (AVE) were at the diagonal, and the values of the squared correlation coefficients were at the non-diagonal. Boldface highlights the diagonals constructs are similar. The results indicated all HTMT values were less than 0.89, which didn't exceed the criteria of 0.9; moreover, the HTMT values are significantly different from 1 in the bootstrapping procedure (Table 1). The results support the presence of the discriminant validity was acceptable.

Finally, information feedback, flow experience, and perceived learning effectiveness formed a concept of second-order formative constructs. They were formed by the weighted sum of their first-order reflective constructs. The principal component analysis weights are better than evaluating by the factor loadings of indicators suggested by Petter et al. (2007). To meet the basic requirements for research analysis, the authors further examined the variance inflation factor (VIF) of all items to avoid excessive multicollinearity, enhancing the validity of the formative model. Table 2 indicates none of the VIFs exceeded the criteria of 3.3 (Petter et al., 2007); thus, serious multicollinearity was not present in this study.

4.3 The validity of structural model

This study uses the bootstrapping procedure by partial least squares SEM to evaluate all hypotheses of the structural model. The authors use nonparametric bootstrapping with 5,000 samples and bias-corrected 95% confidence intervals to assess all hypotheses of the structural model. Additionally, predictive relevance (Q square) can assess the structural model's goodness of fit. According to the studies (Geisser, 1974; Stone, 1974), all endogenous constructs should be above 0. The results of the Q square values ranged from 0.02 to 0.83, which did not include 0. Additionally, Fig. 4 shows the R squared values of flow experience, perceived learning effectiveness, continued intention, and improved learning performance were 0.15, 0.49, 0.49, and 0.03, respectively.

Table 2 Testing the multicollinearity by weight and variance inflation factor (VIF)

Second-order construct	First-order first-construct	VIF	Standard error	Weight (*t*-value)
Information feedback	Feedforward	1.28	0.04	0.42*** (11.92)
	Cognitive	1.69	0.03	0.47*** (15.39)
	Outcome	1.81	0.03	0.34*** (11.10)
Flow experience	Focused	1.38	0.04	0.50*** (11.61)
	Control	1.2	0.05	0.36*** (6.58)
	Enjoyment	1.25	0.05	0.44*** (8.75)
Learning effectiveness	Response	2.1	0.01	0.31*** (20.25)
	Learning	2.09	0.02	0.27*** (18.34)
	Behavior	2.5	0.02	0.27*** (16.08)
	Achievement	2.95	0.02	0.31*** (21.2)

*** $p < 0.001$

5 Conclusion

MARLS incorporate mobile devices and AR applications in the instruction/learning on computer motherboard architecture, allowing learners with a positive flow state to complete their learning tasks, improving perceived learning effectiveness and continued intention. MARLS use visual and tactile information feedback to assist learners in completing their tasks in the learning procedure. The positive flow state can help their absorption, memory, and cognitive abilities. Therefore, appropriate approaches (i.e., strategies, tools, and information feedback) are needed to facilitate learner awareness, reflection, intention, or action. This study suggests new learning material content incorporated into technologically-enhanced learning design could significantly increase perceived learning effectiveness and continued intention among learners of MARLS. Such digitized MARLS facilitate learners' interest and motivation toward learning knowledge of a specific challenging learning area by offering them an interesting and interactive learning environment (Bressler et al., 2021). The finding of this study can provide us with important insight and valuable information for future studies and various stakeholders to use as guidelines for developing new tools.

This study proposed a technologically-enhanced learning process that strengthens learners' perceived learning effectiveness through MARLS to offer suitable learning support by enhancing the understanding of the learning materials. The findings of this study have some implications and limitations described as follows.

5.1 Theoretical implications

In the context of using MARLS in higher educational institutes, this study is among the first group of studies that integrate the theoretical views of information feedback, flow experiences, and cognitive loads to explain how MARLS can positively influence students' perceived learning effectiveness. The validation of the causal relationships among information feedback, flow experience, perceived learning effectiveness, improved learning performance, and continued intention to use MARLS can help us better understand learners' learning experiences and behaviors in AR-based learning environments. The results significantly contribute to the existing literature, and offer implications regarding how the learners in higher educational institutes can be motivated to use the AR-based learning applications that are similar to the MARLS.

To be specific, the research results imply that when the level of the quality of the information feedback of the MARLS is high, the MARLS users can be more immersed in the learning processes (i.e., flow experience), thus resulting in better learning outcomes (Chen et al., 2021; Müller & Wulf, 2022). To elaborate on the statement above, the research results of this study contradicted some of the prior studies (e.g., Burns et al., 2021; Lerch & Harter, 2001; Lin & Wang, 2021; Yen & Lin, 2020) and indicate that information feedback are helpful for supporting learning, as found in some other prior studies (e.g., Kajitani et al., 2020; Eckes & Wilde, 2019; Rodríguez et al., 2022). Those results thus contribute to the theory development of future MARLS studies by confirming the significant positive effects of information feedback on students learning effectiveness in MARLS contexts, and highlight the importance of including the concept of information feedback in future studies that specifically examine the effectiveness of using MARLS to support student learning in various educational contexts, which, to the best of our knowledge, has not been done in prior studies of MARLS.

Additionally, our findings reveal that when the MARLS are easily accessible and provide learners with timely and useful feedback, the learners are more likely to develop a more thorough understanding of the learning subjects. This is because the learners can feel more motivated to learn, be more immersed in the learning tasks, and find the learning processes to be more enjoyable (i.e., flow experience), thus resulting in better learning outcomes (Chen et al., 2021; Müller & Wulf, 2022). Therefore, MARLS users can be benefited by an AR-supported student-centered pedagogical method that can eliminate the obstacles of traditional learning, such as external distractions in the learning environment and less enjoyable learning processes, via the formation of flow experience (Okai-Ugbaje et al., 2022).

Finally, the significant direct and moderating effects of extraneous cognitive loads indicate educators cannot avoid the negative influence of extraneous cognitive loads on the learning process. While digital learning materials and teaching approaches have widely spread to various educational settings nowadays, extraneous cognitive loads' direct and intervening effects cannot be neglected. The extraneous cognitive loads are an obstacle to effective learning, and educators should devote themselves to eliminate the learning materials that may result in increases in learners' extraneous cognitive loads when developing their teaching content and tools.

5.2 Practical implications

This study also has practical implications for instructors, students, and other stakeholders. First, regarding the intervention of extraneous cognitive load, this study suggests researchers and instructors should design and build a clear relationship between the figures, diagrams, and text. In such a case, it may reduce learners' cognitive load and be helpful for them to build learning concepts, facilitating their perceived learning effectiveness.

Second, from the viewpoint of information feedback, MARLS can effectively support instructors' teaching by offering prompt information feedback, in various kinds of format, that may be used as guidelines for learning and eventually contribute to the enhancement of the learners' learning effectiveness. To elaborate on this, using the functions of MARLS helps instructors to monitor the learning progress of students by referring to the MARLS feedback. In such a learning situation, learners can move forward or backward to understand the episode of learning content to deepen their impression. Additionally, instructors may align appropriate teaching approaches (e.g., situational teaching) with the use of information feedback in a MARLS-based educational context. In other words, MARLS are capable of presenting learning instructions (i.e., information feedback) at any stage of the learning processes. Therefore, instructors can thus develop useful feedback and offer it to the learners at the appropriate points of time based on the learners' progress in the MARLS learning processes in order to ensure the learners achieve the focal learning objectives in an effective manner. For example, instructors may use automatic message generation functions that can automatically generate useful information feedback (e.g., feedforward and cognitive feedback) at the appropriate points of time during the MARLS learning processes in order to help students reflect on what is learned and/or concentrate on what is to be learned (Rodríguez et al., 2022), thus enhancing their flow experience and learning effectiveness.

Finally, regarding flow experience, a learner's engagement or immersion in MARLS can symbolize a flow state (Bressler & Bodzin, 2013; Tang et al., 2022). If learners perceive learning tasks involving meaningful experiences, they may maintain a sense of control and pay more focused attention to learning goals. Flow experience promotes learners' perceived learning effectiveness or performance (i.e., decreased technological frustrations, made information or navigation easier by vision-based AR, and enjoyed having to think) and continued intention to use MARLS. In summary, this study revealed the important role that learners' flow experience plays in facilitating learners' learning effectiveness in MARLS-supported educational contexts. Therefore, future MARLS developers should carefully consider how to design the MARLS that adequately align the learning processes with the primary learning objectives, which can eliminate users' learning pressure in order to facilitate the formation of their flow experience and improve their learning outcome (Chang et al., 2022; Kajitani et al., 2020; Skulmowski & Xu, 2022; Yu et al., 2019).

5.3 Limitation

Some limitations exist in this study. The learning material content only focuses on computer motherboard architecture. The results of this experiment suggest future studies could improve learning material content design by incorporating more conceptual diagrams, tables, and quizzes into their experiment planning regarding IT-related or other science curricula. Additionally, the participants only focused on the first-time use of MARLS and the conception of computer motherboard architecture; thus, the technical and practical conceptions are simple. Future study can increase the difficulty in the curriculum with more depth and breadth of materials to strengthen the learners' abilities. Moreover, undergraduate students or above were invited to participate in this study. Concerning the information feedback mechanism of MARLS, subsequent researchers can design the appropriate feedback based on the learners' age, gender, or familiarity levels with computers. For example, using diverse images may stimulate positive emotional responses with complete information feedback for learners. Further, this study uses mobile devices and AR applications for this experiment. Subsequent researchers can combine diverse technologies and techniques to develop a more optimal learning system to strengthen the feasibility and development of potential limitations in various educational settings, including space, time, etc.

Appendix

See Table 3

Table 3 List of survey items of this study

Factor	Item	Factor loading
Feedforward (Brooks et al., 2019)	Before the experiment, providing the…	
	IFF1 knowledge of the computer motherboard architecture was helpful to me	0.87
	IFF2 knowledge of the computer motherboard architecture did not help me learn and better understand it. **	0.78
	IFF3 operational content gave me a preliminary understanding of the relevant knowledge of the computer motherboard architecture	0.82
Cognitive feedback (Maier et al., 2016)	IFC1 I am not interested in the cognitive feedback provided by MARLS. **	0.70
	IFC2 The MARLS can provide detailed feedback on answering questions and that is a great thing	0.91
	IFC3 The MARLS technology can provide detailed feedback on answering questions and that is helpful for me	0.86
Outcome feedback (Faber et al., 2017; Liu et al., 2021)	IFO1 The outcome feedback provided after the exam did not give me a better understanding of computer motherboard architecture. **	0.70
	IFO2 The outcome feedback provided after the quiz made me more familiar with the computer hardware	0.93
	IFO3 The outcome feedback provided after the quiz allowed me to understand better which parts of my knowledge are still lacking regarding computer hardware	0.90
Focused attention (Rodríguez-Ardura & Meseguer-Artola, 2017)	FEF1 I can block out most other distractions when using the MARLS	0.88
	FEF2 I am absorbed in what I am doing when using the MARLS	0.83
	FEF3 I have a feeling of concentration when using the MARLS	0.88
Sense of control (Rodríguez-Ardura & Meseguer-Artola, 2017)	FEC1 I feel in control when I use the MARLS	0.76
	FEC2 I was influenced when I used the MARLS. **	0.85
	FEC3 I was dominated when I used the MARLS. **	0.76
Enjoyment (Ahn et al., 2007; Buil et al., 2019)	FEE1 I really enjoyed it when I used the MARLS	0.84
	FEE2 I felt good when I used the MARLS	0.90
	FEE3 Using the MARLS made my learning task more fun	0.89

Table 3 (continued)

Factor	Item	Factor loading
Response (Chrysafiadi & Virvou, 2013)	LER1 MARLS helps me understand the concept of computer motherboard architecture	0.78
	LER2 I think MARLS are useful as general educational tools	0.85
	LER3 I understand all the learning content while using the MARLS	0.75
Learning (Huang et al., 2015)	LEL1 I think MARLS can make mainframe computer motherboard architecture courses more interesting	0.87
	LEL2 I think courses on MARLS are worth trying	0.88
	LEL3 If everyone is serious about their studies, I think they will complete the computer motherboard architecture quiz in MARLS	0.80
Behavior (Chrysafiadi & Virvou, 2013)	LEB1 MARLS affect my positive perception of the computer motherboard architecture	0.86
	LEB2 MARLS inspired me to learn more about computer motherboard architecture	0.81
	LEB3 MARLS affect my positive perception of other AR learning courses	0.83
Achievement (Chrysafiadi & Virvou, 2013)	LEA1 MARLS helped me learn other computer mainframe architecture-related courses	0.91
	LEA2 MARLS helps me learn	0.90
	LEA3 MARLS helped me become more aware of other activities related to learning about computer motherboard architecture	0.90
Extraneous cognitive load (Leppink-Heuvel & van den Heuvel, 2015)	ECL1 Instructions and explanations in the MARLS Interactive Learning course are of no avail to aid learning	0.88
	ECL2 I find the instructions and explanations in the MARLS interactive learning course incomprehensible	0.91
	ECL3 In this MARLS interactive learning course, I put a lot of effort into understanding the unclear instructions and explanations	0.75
Continued intention (Mohammadyari & Singh, 2015)	CI1 I will continue to use MARLS	0.92
	CI2 I will continue to use MARLS rather than traditional learning methods	0.88
	CI3 If possible, I would like to stop using MARLS. **	0.71
Improved learning performance	DLP1 The normalized scores of the post-test minus pre-test	1

** reverse score

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Declarations

Conflict of interest None

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