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Influencing factors on students' learning effectiveness of AI-based technology application: Mediation variable of the human-computer interaction experience

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Abstract
This research investigated 1,552 university students to explore the correlation between their learning effectiveness of artificial intelligence (AI) technology application and its influencing factors. The aim is to provide a reference for school planning and application of AI in information and communications technology (ICT) teaching. The results show that ICT self-efficacy (ICT-SE) has a significant direct effect, and human-computer interaction experience (HCIE) has a significant indirect effect on lLearning effectiveness of AI-based technology applications (LE-AITA). The impact model of university student ICT-SE and HCIE on LE-AITA exhibits a good fit. The recommendation is that Taiwan education improve the AI learning environment, provide a suitable platform for the use and development of educational technology, and create a seamless teaching and learning experience. We discuss influencing factors and provide suggestions for the development of AI education.

Keywords Learning effectiveness of AI-based technology application (LE-AITA) · human-computer interaction experience (HCIE) · information and communications technology (ICT) · information and communications technology self-efficacy (ICT-SE)

1 Introduction

Changes in the social structure and information technology's emergence of new demands have become important for the application of AI information technology in Taiwan. Taiwan is moving towards becoming a smart country, ranking 11th in the world's digital competitiveness evaluation in 2020 (Netherlands Innovation Network in Taiwan, 2020). In fact, about 29% of Taiwan's current GDP

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Extended author information available on the last page of the article is forecast to be related to digital technology by 2025 (Taiwan Executive Yuan, 2021; Taiwan News, 2021).

One study surveyed a total of 247 companies in 10 Taiwanese business areas and found that more than 80% of them have tried to apply AI into their businesses, and 25% of companies have actively applied AI and expanded their proportion (Epoch Times, 2021). Among them, AUO Digital Technology Company has utilized thousands of AI prediction models, in which 48% are used to improve efficiency, 38% are used for process control, and the rest are used for equipment maintenance early warning. The impact of AI's introduction in the company includes improving human efficiency and production yield and saving production costs of more than NT$10 billion (Epoch Times, 2021; Taiwan Industrial Technology Research Institute, 2021). In response to the advent of the AI era, grasping the opportunities of AI development and training AI talents has become the focus of the industry. Taiwan is promoting the AI New Generation Talent Training Program (AIGO) to meet the needs of industrial AI talents and to help train industrial intelligent technology integration and innovative application talents (Future City, 2021; Taiwan Bureau of Industry, 2021). It can be seen that nurturing students to have AI capabilities to meet the needs of enterprises for AI manpower is one of the top current university education goals.

AI information technology refers to the use of appropriate digital media, including information technology, Internet, satellite broadcasting, optical discs, and other related software and hardware facilities. It is important through barrier-free information transmission to obtain digital teaching materials, carry out correct effective online or offline learning activities create meaningful learning experiences, and achieve learning goals (Ahmad et al., 2020; Cox, 2021; Liu & Wang, 2020). The application of AI in education learning style that uses AI information technology breaks the gap between physical space and time constraints and the current socio-economic situation and makes full use of the characteristics of the Internet. Learners who apply AI information technology can reduce learning costs and help them become more diversified. Under the system of distance education, teachers and students are no longer confined to time and space, and online learning has also received more and more attention due to changes in the social environment (Maqableh & Jaradat, 2021; MUhie & Woldie, 2020; Schiff, 2021).

The AI-based technology application used in teaching and learning is for the guidance of automatic grading and formative evaluation of students. The decline in conventional tech-enabled instructional design research and the flourishing of student profiling models and learning analytics has spurred personal tutors, intelligent support for collaborative learning, and intelligent virtual reality categories of AI software applications in education (González-Calatayud et al., 2021; Guan et al., 2020; Luckin et al., 2016; Zawacki-Richter et al., 2019). With so many AI technology applications, teachers have their own reasons for choosing those AI-based technology applications in education, including MOOCs of Coursera, Udacity, and EDX, which are used to improve online learning courses and learning services. The "Dualingon, Babbel, Rosetta Stone APP" is a learning language application for formal and informal use, while the "Turnitin, Writelab, PEG Writing, Write to

Learn" is a system with writing, feedback, and scoring through machine learning (Kaplan & Haenlein, 2016; Podgoršek et al., 2019).

The curriculum must meet the needs of the times to incorporate digital technology and new thinking, so that the learning style of using AI information technology is born accordingly (Maqableh & Jaradat, 2021; Zawacki-Richter et al., 2019). Universities are eager to keep up with this wave of changes based on virtual reality/augmented reality. The use of virtual reality (VR) and augmented reality (AR) in educational occasions can help expand students' imagination and enhance their sense of reality of the learning environment (Criollo et al., 2021; Kaplan & Haenlein, 2016; Reljić et al., 2021; Stojsic et al., 2020). Therefore, in response to information technology, only the combination of technology and curriculum can enable the sustainable development of higher education.

There are many factors affecting LE-AITA, such as self-directed learning, learning motivation, and ICT attitude (Ardito et al., 2021; Owoc et al., 2021; Martin, 2021; Mozer et al., 2019; MUhie & Woldie, 2020; Siswa, 2020; Zawacki-Richter et al., 2019). Student learning factors are significantly related to LE-AITA, showing the richness of teaching materials design and curriculum interaction strategies. Influencing factors such as student management, student information literacy, and system and network quality are relevant to students' participation in AI information technology (Al-Rahmi et al., 2021; Al-Said & Al-Said, 2020; Ehrenbrink & Möller, 2018). Studies at home and abroad believe that the teacher-student relationship has a significant influence on face-to-face teaching effectiveness. It also has a significant impact on the effectiveness of student learning (Martin, 2021; Mozer et al., 2019). Research has shown that school factors, student learning factors, and textbook factors are significantly related to LE-AITA (Martin, 2021; Mozer et al., 2019; MUhie & Woldie, 2020; Siswa, 2020). Researchers use online learning experience and teaching system quality and design to measure teachers' satisfaction with participating in AI information technology learning (Ardito et al., 2021; Wang & Wang, 2019; Zawacki-Richter et al., 2019). Therefore, this research intends to understand the important factors that affect students' LE-AITA from their perspective (Al-Said & Al-Said, 2020; Tsai et al., 2021; Tussyadiah & Miller, 2019).

Based on the above, this study focused on factors that could help explain why some students elect to use AI in learning and how it impacts their learning effectiveness. Therefore, this research takes university students as the research object and analyzes the factors that affect their LE-AITA and their relationship with influence factors. The results can be used as a reference for LE-AITA vendors and university teachers' curriculum design.

1.1 Research purposes

This study aims to explore the variables that may influence students' learning effectiveness of AI-based technology application (LE-AITA) and to find the relationships among the variables of ICT-SE and HCIE. The purposes of this study are to address the following two issues.

1. To explore the relationships between students' perceived ICT-SE, HCIE, and LE-AITA.
2. To identify a suitable model that can identify important implications and strengthen university students' LE-AITA.

2 Literature review

2.1 Learning effectiveness of AI-based technology application and its influencing factors

The learning effectiveness of AI-based technology application (LE-AITA) refers to students' use of ICT digital tools to obtain digital teaching materials through electronic media such as the Internet, mobile phones, and multimedia such as video and sound, in order to conduct online or offline learning activities which knowledge, skills, and affection have been acquired (MUhie & Woldie, 2020; Siswa, 2020; Tang & Austin, 2009; Tuomi, 2018; Wang & Wang, 2019). When students have problems to be solved or want to obtain certain skills and information, they will pursue relevant information to solve the problem and achieve the goal. At the same time, they will evaluate the acquired skills, concepts, and knowledge (Martin, 2021; Mozer et al., 2019; MUhie & Woldie, 2020; Siswa, 2020). Learning effectiveness of AI-based technology application (LE-AITA) includes three levels: learning autonomy, learning performance, and learning satisfaction (Ardito et al., 2021; Owoc et al., 2021; Tang & Austin, 2009; Tuomi, 2018; Wang & Wang, 2019; Zawacki-Richter et al., 2019).

First, "learning autonomy" refers to the learning input, energy, and effort invested by individual students in the process of autonomy participating in learning (Fahimirad & Kotamjani, 2018; Oudeyer, 2019). Ardito et al. (2021) indicatedthat more open and high levels of student-centric autonomy learning activities are associated with learning networks. There are highly decentralized and epistemic spaces that have built a social learning platform based on Elgg software. Student participation in learning has an important impact on learning growth. Learning participation refers to the intensity and emotional quality input of students when they start and perform learning activities. They often participate in the course discussion area to discuss related topics (Martin, 2021; MUhie & Woldie, 2020; Rahoo et al., 2021; Rajabalee & Santally, 2020; Schiff, 2021).

Second, "learning performance" refers to students appropriately improving their learning motivation based on their own learning experience, so as to enhance learning outcomes and achieve learning goals (Che et al., 2021; Schiff, 2021). Wang and Zheng (2021) pointed out an AI-based application plays an active role and has an effect on teaching concepts and teaching platform construction. AI information technology has the characteristics of openness and interactivity. Digital learning not only can achieve the purpose of spreading and sharing knowledge but also can activate and update knowledge through high-level discussion and interaction (Shehzadi et al., 2020; Yunusa & Umar, 2021). Students have to construct an exclusive learning environment according to their own needs and habits, adjust or strengthen them appropriately according to the learning situation with student-oriented characteristics, and use AI information technology to improve their learning effectiveness (Chen et al., 2021; Mlambo et al., 2020; Rahoo et al., 2021; Sahin & Yilmaz, 2020).

Third, "learning satisfaction" denotes students' feelings or attitudes towards learning activities, about the content, methods, process, and results of AI information technology learning activities, and their internal subjective feelings (Owoc et al., 2021; Tuomi, 2018). Fahimirad and Kotamjani (2018) considered the LE-AITA learning goal and how it may cultivate responsible citizens and ICT-educated minds. When teachers teach new AI learning, students insist on some factors such as creativity, imagination, innovation, and skills, which are almost impossible to perform by machines.

With regard to LE-AITA influencing factors, Chen et al. (2021) results showed that the students not only made significant progress in learning effectiveness, but also in particular made significant improvements in two parts: electromechanical concepts and image recognition knowledge including active learning, and self-efficacy after confirming. Wang et al. (2019) results obtained from this study observed that computer self-efficacy and enjoyment as intrinsic motivations significantly predict continuance intention, while perceived ease of use, perceived usefulness and user perception were insignificant. This outcome implies that computer self-efficacy and enjoyment significantly affect the willingness of students to continue using Cloud e-learning application in their studies. Wang et al. (2021) analyze teacher adoption of AI-based applications and find self-efficacy positively influences perceived ease of use and attitude towards adopting such applications. Their research indicated that enhancing teachers' self-efficacy could reduce their anxiety towards using AI-based applications in their teaching (Wang et al., 2021; Yang, 2021). The ICT-SE and performance have a positive result, and after summarizing the above literature, we know that students' own ICT-SE is the main factor affecting LE-AITA (Hatlevik et al., 2018; Mlambo et al., 2020; Musharraf et al., 2018; Zawacki-Richter et al., 2019).

According to research, Oudeyer (2019) believes students can use learning logs or graphs to track their progress, and teachers can analyze teaching errors and help students use the errors as learning opportunities to adapt to their learning goals. In AI-based learning for students, the Item Response Theory (IRT) intelligent robots with adaptive learning capabilities will play a key task (Chaudhry & Kazim, 2021; Chen et al., 2020). During the learning process, they take part in the overall learning activities of AI-based information technology, such as system quality, course content design, course interaction strategies, and network quality (Schiff, 2021; Yen et al., 2018; Zawacki-Richter et al., 2019).

HCIE is applied in the field of education and learning to improve students' LE-AITA, and can be based on suitable learning agent platforms, intelligent agents, and joint learning application scenarios (Ardito & Betül, 2021; Chaudhry & Kazim, 2021; Chen et al., 2020). In terms of constructing a smart and adaptive learning cloud platform features include: smart and adaptive learning robot AI software system, building IRT student learning parameters, integrating Facebook AI Research (FAIR) computer Go program Darkforest, and deep learning Go open source software, build an open source Go DarkForest learning system with dynamic learning function, and combine with Brain Computer Interface (BCI) to build a human-computer co-learning system. It can be effectively promoting students' LE-AITA that combining physical robots in the field of future education and learning, constructing an AI-based educational learning innovation model, and constructing a smart learning environment that integrates virtual and reality (Al-Rahmi et al., 2021; Ardito & Betül, 2021; Chaudhry & Kazim, 2021; Chen et al., 2020). Based on the above, The HCIE and performance have a positive result, and after summarizing the above literature, we know that students' own HCIE is the main factor affecting LE-AITA.

2.2 ICT self-efficacy as a predictor of learning effectiveness of AI-based technology application

ICT self-efficacy (ICT-SE) refers to a student's self-judgment ability of using information technology, which is a kind of confidence in their ICT skills, ICT attitude, and ICT cognition (Alahakoon & Somaratne, 2020; Hatlevik et al., 2018; Mlambo et al., 2020; Musharraf et al., 2018; Rohatgi et al., 2016). Hatlevik et al. (2018) indicated self-efficacy is an important concept for understanding learning and achievement. The self-efficacy concept covers students' self-confidence and their expectations for future performance. Their learning experiences are crucial for the development of self-efficacy beliefs, which may affect their own achievements (Hatlevik et al., 2018; Wang et al., 2021; Şendurur & Yılıdrım, 2019; Yu, 2007).

First, the "ICT skill" is the ability to operate information technology, including the application of information technology and the use of peripheral equipment, data processing, and network operation capabilities (Hatlevik et al., 2018; Rohatgi et al., 2016; Wang et al., 2021). Becoming more familiar with the technology-mediated learning environment will significantly affect students' self-efficacy and learning effectiveness. When students are proficient in an ICT skill, it is helpful to improve the learning of AI information technology (Alahakoon & Somaratne, 2020; Mlambo et al., 2020).

Second, "ICT cognition" refers to the basic knowledge of information technology (IT) possessed by students, focusing on the basic concepts of information technology, the use of software and hardware, and the Internet (Nayanajith & Damunupola, 2021; Paul & Jefferson, 2019). From the viewpoint of the Planned Behavior Theory (PBT), students' ICT-SE refers to their learning behavioral decision-making under the rational action theory, which considers time and opportunity and other factors of Perceived Behavioral Control (PBC) and for which students have sufficient ICT cognition control ability (Ajzen, 2020; Choi & Park, 2020). Students' ICT cognition is used to complete the task of learning by using AI information technology as a tool and to assist in learning various things that include Adaptive-Learning Platform (因材網), Taipei Cool Class, Voice-tube, Augmented Reality, I-Reading, Amazon Alexa Echo, Coursera, Udacity, EDX, and Thinkster (Junyi Educational Learning Platform, 2021; Ministry of Education, 2021). Students taking the "VoiceTube's Hero" course experience a rich and diverse amount of interesting theme videos. The unique AI intelligent learning system can tailor the best exclusive courses according to each person's level so that students can better effectively learn authentic English.

Students also have used the Adaptive-Learning Platform (因材網) that provides free high-quality learning resources of 50,000 teaching videos and exercises. Research has shown when students understand the functions of the technology-media teaching system that they are able to provide a quick response, correct ICT cognition, and give communication assistance during the learning process (Al-Said & Al-Said, 2020; Ardito & Betül, 2021; Asthana & Hazela, 2020; Mlambo et al., 2020). From the above, it has also shown that current online courses should have pre-requisite capabilities, showing that ICT cognition has an impact on teaching effectiveness.

Third, related research has pointed out that the attitude of students is significantly related to the use of ICT (Guillén-Gámez et al., 2020; Nazari et al., 2021). Moreover, attitude affects one's interest in learning, as a positive ICT attitude will increase the chance of success in IT learning, while a negative ICT attitude will reduce the interest in learning IT. Students' attitudes towards information technology and teachers' effectiveness of teaching in a network-oriented learning environment are also important factors (Guillén-Gámez et al., 2020; Mlambo et al., 2020). Nazari et al. (2021) examined an AI digital writing assistant in higher education and found that AI-driven writing tools are effective through the formative feedback and evaluation of non-native English academic writing students. Such tools can promote the ICT-SE of learning behaviors and attitudes. ICT attitude refers to a student's degree of perception of like or dislike of information technology and a persistent and consistent behavioral tendency toward said technology. Research has found that students with higher ICT-SE have stronger intentions to learn and use information technology (Musharraf et al., 2018; Nayanajith & Damunupola, 2021; Yusop et al., 2021).

Regarding ICT-SE self-efficacy as a predictive indicator of LE-AITA, pleasant or successful experience will increase students' use and expectations of the system, and their individual motivation to participate in the adoption of the system will increase. The research results also point out that ICT-SE is an important variable for predicting the use of information technology (Alahakoon & Somaratne, 2020; Mlambo et al., 2020). Based on the above, it can be seen that if students have an ability in ICT-SE, then they will benefit from learning to use AI-based information technology. Therefore, this research regards ICT-SE as one of the factors affecting university students' participation in LE-AITA, which deserves further investigation.

2.3 Human-computer interaction experience as a mediator on learning effectiveness of AI technology application

The human-computer interaction experience (HCIE) refers to making it easier for students to use all kinds of information technology to accomplish their goals, which include creating students' positive human-computer interaction experience, ensuring they can easily navigate the site/device and find what they are looking for, and creating content that is understandable and accessible to them (Balakrishnan & Dwivedi, 2021; Che et al., 2021; Seo et al., 2021; Yang, 2021). Students' experience in using technology is an important key to the popularization and application of ICT skills that includes line pens, smart speakers, online games, interactive devices, robots, social media, virtual reality (VR), augmentation reality (AR), Internet of Things (IoT), etc. (Al-Said & Al-Said, 2020; Ehrenbrink & Möller, 2018).

HCIE is a spontaneous LE-AITA learning method, and it emphasizes the self-arranged learning mode. Thus, it is related to self-directed learning attitude (Che et al., 2021; Xu et al., 2021 ; Zhou et al., 2021). Through self-directed learning, students can decide learning materials and learning methods according to their own needs or problems to be solved (Oberländer et al., 2020; Pillai et al., 2021; Rajabalee & Santally, 2020). Therefore, self-directed learning opens up multiple HCIE learning channels, makes learning opportunities highly flexible and open, and uses AI information technology learning to place more emphasis on effective exploration and autonomous learning than traditional classroom contextual learning. Whether students can trigger effective self-exploration and autonomous learning in a digital environment will determine the effectiveness of their LE-AITA (Rajabalee & Santally, 2020; Sahin & Yilmaz, 2020; Schiff, 2021).

From the viewpoint of the user experience (UX) models, UX Designer and UX Researcher in the field of HCIE industry aim to discuss the user interface design that takes into account the aesthetics, readability, and fluency of the interface itself, as well as the experience and environment that various use processes bring to the user (Hornbæk & Hertzum, 2017; Yang et al., 2020). Taiwan schools use the "Internet of Things and Campus Wisdom System Integration Application" curriculum to combine life technology, information technology, earth sciences, and fine arts courses in order to learn about emerging technologies, such as AR, VR, Internet of Things (IoT), artificial intelligence, and big data and to cultivate future talents in the field of science and technology. Letting students use IoT, 3D printing, laser cutting, and other emerging technologies to cooperate with IT computing thinking and programming can create a campus smart system, and art teachers will then be able to integrate aesthetic education and modeling design. AI smart systems have become the learning content of campus beautification (Xu et al., 2021; Zhou et al., 2021).

The viewpoint of the Technology Acceptance Model (TAM) advocates that influencing students' usefulness and ease of use in HCIE cognition will affect their attitude toward using technology and thus impact specific behavior (Hornbæk & Hertzum, 2017; Oberländer et al., 2020; Pei & Wu, 2019). The intention to use is not only affected by the attitude used, but also by the usefulness of the cognition. Students feel that the use of AI information technology will help their future learning performance, which will directly affect their willingness to use this technology (Rajabalee & Santally, 2020; Zhou et al., 2021). Understanding the mechanisms that shape the adoption and use of information technology is central to human-computer interaction. Incorporating experiences is important because these emotions and experiences are common in the practical adoption and use of technology (Hornbæk & Hertzum, 2017).

From the above, HCIE includes three levels: perceived usefulness, perceived usability, and interpersonal interaction (Al-Said & Al-Said, 2020; Ehrenbrink & Möller, 2018; van Schaik & Ling, 2005). First, according to the research of Davis (1989), "perceived usefulness" is defined as the degree to which users believe that the use of new technology is useful for improving work efficiency. Chang et al. (2021) showed that perceived usefulness contexts affect all variables associated with gratifications-obtained and gratification-opportunities. With the exception of social integrativeness, all other gratification-based factors significantly affect attitude. Attitude in turn significantly influences learning performance and continuous use intention (Chang et al., 2021; Cox, 2021; Ehrenbrink & Möller, 2018). Second, "perceived usability" is defined as the degree to which users think new technology is easy to learn and use. Students believe that using digital tools in online activities is easy to use, and that such activities are conducted in a way that can help improve learning effectiveness (Chang et al., 2021; Cox, 2021; Owoc et al., 2021). Third, "interpersonal interaction" refers to activities such as discussion, observation, and cooperative learning between people. Hornbæk & Hertzum (2017) propose hedonic versus utilitarian settings on the importance of the experiential influence component for its role in adoption and use. From an HCI perspective, Xu et al. (2021) state that AI systems can exhibit unique machine behavior and evolve to gain certain levels of human-like cognitive, self-executing, and self-adaptive abilities. It is important that, driven by the unique characteristics of AI technology, AI systems may evolve from an assistive tool that primarily supports human operations to a collaborative teammate, building a new form of human-machine collaborative relationship as AI technology advances (Balakrishnan & Dwivedi, 2021; Seo et al., 2021; Yang et al., 2020).

Based on the above, teachers' role will be the orchestration of AI and other digital tools and environments that HCIE applied in teaching of students' LE-AITA. The future scenarios of AI in teaching and learning suggest that AI-based technology can be used as a toolkit to enable teachers and students to use different kinds of services and to combine different intelligent tools that will be developed in the future.

3 Methodology

3.1 Participants

Stratified clustering and random sampling method were used for university students. The stratified sampling is in accordance with the basic information (e.g., gender, grade, professional fields, AI information technology learning experience, and do you have information equipment at home) and randomly selected a sample of departments by computer. Taiwan's Ministry of Education Statistics (2021a) calculated that 152 universities and 1,203,460 students make up this study group. The present study adopted professional field random sampling and selected 10 professional fields. The respondents are students of 26 university schools, stratified by region and professional field networks. In this population, there are 13 public and 13 private universities (Taiwan's Ministry of Education Statistics, 2021b). Krejcie and Morgan (1970) calculated the actual number of questionnaires for sampling at 356. This study used 500% sampling; proportional sampling made up 1784 people. In total, 1784 questionnaires of the formal scale were distributed, and 1552 effective questionnaires were returned, for a valid questionnaire response rate of 87%. Table 1 shows the respondents' gender, grade, professional fields, AI-based information technology learning experience, and whether they have CIT equipment at home.

Table 1 Distribution of students' background in formal scales (N=1552)

Participant demographics	Frequency	%
Gender		
1. Male	740	47.7%
2. Female	812	52.3%
Grade		
1. Freshman	363	23.3%
2. Sophomore	379	23.8%
3. Junior	394	25.4%
4. Senior year (inclusive above)	426	27.4%
Professional fields		
1. Education field	70	4.5%
2. Arts and Humanities	188	12.1%
3. Social sciences, journalism and books and information fields	85	5.5%
4. Commercial, management and legal fields	281	18.1%
5. Natural science, mathematics and statistics	96	6.2%
6. Information and Communication Technology	126	8.1%
7. Engineering, manufacturing and construction	304	19.6%
8. Agriculture, forestry, fishery and veterinary industry	67	4.3%
9. Medicine, health and social welfare	158	10.2%
10. Service area	160	10.3%
11. Other areas	17	1.1%
AI-based information technology learning experience		
1. One year (inclusive)	930	53.5%
2. Two years	306	19.6%
3. Three years	256	16.5%
4. Four years (inclusive above)	92	10.4%
Do you have information equipment at home		
1. Have	1516	97.7%
2. no	36	2.3 %

The participants were recruited by the school administration, and the questionnaires were distributed by the teachers. Before they responded to the questionnaire, the teachers were given a guidebook explaining how to complete the survey. The average time spent on completing the questionnaire was within 30 minutes. Participants gave informed consent before the study commenced.

3.2 Measurement

A 40-item survey questionnaire was developed to measure participants' HCIE, ICT-SE, and LE-AITA. The research tool is a 'Questionnaire of Factors Which Influence Students' Learning Effectiveness of AI Technology Application'. The questionnaire used in this research is based on the Unified Theory of Acceptance and Use of Technology (UTAUT model), referring to Sezer and Yuilmaz (2019) to develop the "Learning Management System Acceptance Scale" there is four factors: performance expectancy, effort expectancy, facilitating conditions, and social influence). Tezer and Soykan (2017) developed a new technology application acceptance scale of "Acceptance Scale of Tablet Computers by Secondary Education Students" as a measure of the acceptance of AI innovation technology. This survey form is comprised of six factors are: perceived ease of use, perceived usefulness, attitude towards use, social influences, perceived interaction, and intention to adopt. Based on the viewpoints of artificial intelligence and response to positive behavior changes proposed by Tussyadiah and Miller (2019) and refer to "The Students' Perceptions of Technology Scale (SPOTS)" developed by Tang and Austin (2009). The "AI anxiety scale (AIAS)" developed by Wang and Wang (2019), its scale has four factor: learning, job replacement, sociotechnical blindness, and AI configuration. Şendurur and Yılıdrım (2019) developed "Teachers' Computer Self-Efficacy Scale" five factors: Use of Internet and computer for support, Technical knowledge, Office programs and their applications, Classroom applications, and Advance computer use. The "Online Learning Environment Self-Efficacy Scale" developed by Yu (2007) has three factors, namely, previous computer experience, computer self-efficacy and the concept of computer self-ability. The questionnaire includes a HCIE scale, ICT-SE scale, and LE-AITA scale (Alahakoon & Somaratne, 2020; Ehrenbrink & Möller, 2018; Mlambo et al., 2020; Musharraf et al., 2018; Zawacki-Richter et al., 2019). In terms of reliability, this study estimates the Cronbach's α coefficient based on the above analysis results, and the analysis results are shown in Table 2. The contents are described as follows.

1. ICT-SE scale: Its scale includes three constructs: ICT skill (6 items, Cronbach's α= .898), ICT attitude (4 items, Cronbach's α= .834), and ICT cognition (4 items, Cronbach's α= .795). The ICT-SE scale was built on the research tools of Alahakoon and Somaratne (2020), Mlambo et al. (2020), Musharraf et al. (2018), Şendurur and Yılıdrım (2019), Tussyadiah and Miller (2019), and Yu (2007). The scale was designed to investigate the important factors that cause a person to perceive and accept ICT in order to perform specific computer-related tasks. The scale's reliability in terms of Cronbach's α coefficient is .855.
2. HCIE scale: Its scale includes two constructs: perceived usefulness (6 items, Cronbach's α=.892), perceived usability (5 items, Cronbach's α=.911). The HCIE scale was built on the research tools of Ehrenbrink and Möller (2018), van Schaik and Ling (2005), Al-Said and Al-Said (2020), Sezer and Yuilmaz (2019), Tang and Austin (2009), and Yu (2007). The scale was designed to investigate the important factors that cause a person to perceive and interface between him/herself and information technology. The scale's reliability in terms of Cronbach's α coefficient is .882.
3. LE-AITA scale: Its scale includes three constructs: (1) learning autonomy (4 items, Cronbach's α=.851); the question items is: I often learn the textbooks of elective courses online, and often participate in the course discussion area to discuss related topics. (2) learning performance (4 items, Cronbach's α=.871); the question items is: The autonomous learning method of AI information tech-

Table 2 An overview of factors, number of questions, reliability and validity of scale.

Composition of scales	No. of items	Factor loading	Cronbach α	Accumulated explained variance	Kmo	Total reliability Cronbach α
ICT-SE Scale						
ICT 1: ICT skill	6	28.88%	.898	67.24%	.804	.855
ICT 2: ICT attitude	4	19.73%	.834			
ICT 3: ICT cognition	4	18.63%	.795			
HCIE Scale						
HCIE 1: perceived usefulness	6	27.99%	.892	72.77%	. 838	.882
HCIE 2: perceived usability	5	26.93%	.911			
HCIE 3: interpersonal interaction	3	17.85%	.880			
AAI-ITL Scale						
LE-AITA 1: learning autonomy	4	24.92%	.851	71.31%	.812	.898
LE-AITA 2: learning performance	4	23.64%	.871			
LE-AITA 3: learning satisfaction	4	22.75%	.829			

nology has improved my learning effectiveness, and the learning method of AI information technology that is not restricted by time and space has improved my learning effectiveness. (3) learning satisfaction (4 items, Cronbach's α=.829); the question items is: I am satisfied with the content design of AI information technology courses, and I am satisfied with the interactive strategies of AI information technology courses. The LE-AITA scale was built on the research tools of Wang & Wang (Wang & Wang 2019), Tang and Austin (2009), Sezer and Yuilmaz (2019), Zawacki-Richter et al. (2019). The scale was designed to investigate the important factors that cause a person to perceive and use ICT digital tools to learn knowledge, skills, and affection. The scale's reliability in terms of Cronbach's α coefficient is .898.

3.3 Data analyses

This study uses SPSS and LISERL to analyze the data, mainly through descriptive statistics and linear structure analysis to verify the correlation between ICT-SE and HCIE with various aspects of LE-AITA and their impact. Table 3 shows the test of the normal distribution of related factors in the study model. According to the data in the table, all observation variables have non-normal distributions ($p<.05$), but multivariate items are normal. The test has reached a non-significant level ($p>.05$), indicating that it is a normal distribution. The sample data in this study meet the assumptions of applying the most likely approximation method (ML).

Table 3 A test of variables' means, standard deviations and normal distributions

Variable	Mean	Standard deviation	Skewness	Kurtosis	χ^2	p-value
ICT-SE	3.74	.377	-.006	.374	772.278	.000
ICT 1: ICT skill	4.23	.605	-.518	-.222	643.959	.000
ICT 2: ICT attitude	2.77	.841	.293	.294	676.356	.000
ICT 3: ICT cognition	3.99	.762	-.599	.206	784.742	.000
HCIE scale	3.58	.488	-.314	.793	637.603	.000
HCIE 1: perceived usefulness	3.62	.668	-.101	.323	739.155	.000
HCIE 2: perceived usability	3.67	.719	-.304	.330	847.464	.000
HCIE 3: interpersonal interaction	3.36	.863	-.284	.146	885.995	.000
LE-AITA scale	3.51	.664	-.031	.073	483.892	.000
LE-AITA 1:learning autonomy	3.59	.775	-.164	-.147	615.521	.000
LE-AITA 2: learning performance	3.50	.777	-.192	.179	705.366	.000
LE-AITA 3: learning satisfaction	3.44	.766	-.115	.252	854.992	.000
Overall	3.62	.402	-.082	.231	516.892	1.000

4 Result

4.1 Data inspection

This study uses LISERL for model verification that the estimated parameters of this study have reached a significant level. The values of various parameters are shown in Table 4.

4.2 Overall fit

It can be seen from the above that the overall degree of adaptation can be evaluated by three types of measurement indicators: absolute adaptation amount, value-added adaptation amount, and simple effect adaptation amount. This study was estimated by LISERL, and its various indicators are shown in Table 5.

First, it can be seen that $\chi 2$=102.71 and p<.05 in this research model, reaching a significant level. Verification is easily affected by the number of samples and normality of the data. Therefore, when evaluating the overall suitability of the model, other indicators must be added to continue the comprehensive judgment.

Second, in the detection index of absolute fit, Scott (1994) pointed out that the range of GFI value is between 0 and 1. When GFI is closer to 1, the model suitability is better. Generally, the recommended value is above 0.90. This model's GFI= 0.95, and so the display mode is acceptable; AGFI= 0.90, which is greater than the acceptance value recommended by Scott (1994) of 0.9, showing that this model is accepted; RMSEA= 0.09, or less than <0.1, and so the display model is acceptable.

In the index of value-added adaptation amount and simple effect adaptation amount, from the detected data NFI= 0.95, the acceptance value is greater than 0.9, and so the display mode is acceptable; IFI= 0.96, the acceptance value is greater than 0.9, and so the display mode is acceptable; CFI= 0.96, the acceptance value is

Table 4 Tests of variables' means, standard deviations and normal distributions.

Parameter	Standardized coefficient	Standard error	t value	Parameter	Standardized coefficient	Standard error	t value
λ_1	0.61	-	-	δ_1	0.23	0.02	10.56
λ_2	-0.48	0.17	-6.99*	δ_2	0.59	0.05	12.34
λ_3	0.63	0.16	8.21*	δ_3	0.36	0.04	10.08
λ_4	0.75	-	-	δ_4	0.21	0.02	10.66
λ_5	0.75	0.07	14.37*	δ_5	0.23	0.02	10.55
λ_6	-0.25	0.10	-4.69*	δ_6	0.79	0.06	13.98
λ_7	0.72	-	-	ε_1	0.30	0.03	11.85
λ_8	0.87	0.08	15.81*	ε_2	0.14	0.02	7.47
λ_9	0.76	0.07	14.25*	ε_3	0.24	0.02	11.20

*p<.05

Table 5 Overall goodness of fit test results of LE-AITA influence pattern (N=1552)

Type of fitness	Fit index	Evalu-ation standard	Analysis of results not researched	Goodness of fit
Absolute fitness volume	χ^2/d.f.=4.28	<5	Hair (1998)	Acceptable
	GFI=0.95	>0.9	Scott (1994)	Acceptable
	SRMR=0.05	<0.1	Scott (1994)	Acceptable
	RMSEA=0.09	<0.08	Hu and Bentler (1999)	Moderate fit
Incremental fitness	AGFI=0.90	>0.8	Jarvenpaa et al. (2000)	Acceptable
	NFI=0.95	>0.9	Bentler and Bonett (1980)	Acceptable
	NNFI=0.94	>0.9	Bentler and Bonett (1980)	Acceptable
Parsimonious fitness	PNFI=0.63	>0.5	Bentler and Bonett (1980)	Acceptable
	PGFI=0.50	>0.5	Bentler and Bonett (1980)	Acceptable
	CFI=0.96	>0.9	Bagozzi and Yi (1988)	Acceptable
	IFI=0.96	>0.9	Bentler and Bonett (1980)	Acceptable

greater than 0.9, and so the display mode is quite acceptable; PNFI= 0.63, PGFI= 0.50, the acceptance value is greater than 0.5, and so the display model is acceptable.

On the whole of models, in terms of the absolute amount of adaptation, the degree of adaptation is relatively good, while the index of value-added adaptation and simple-efficiency adaptation shows are acceptable. In summary, the data model of this study is an adaptation, which conforms to the empirical data model as a whole, and the degree to which the theoretical model can explain the empirical model is also an adaptation.

4.3 Structural fit

Regarding the structural fit of the model, Hair Jr. et al. (1998) believed that it should be evaluated from the significance test of the structural parameters in the model detection and the R2 value of the potential dependent variable. The R2 value of the potentially dependent variable must be higher than the evaluation standard of 0.5.

According to Table 5, the detection of the structural adaptation of the research model first affects the various structural parameters in the models of ICT-SE, HCIE, and LE-AITA. The effectiveness reaches a significant level ($t>1.96$, $p>.05$), and for the evaluation of potential dependent variable R2, the three potential variables of ICT-SE, HCIE, and LE-AITA are 0.33, 0.40, and 0.48, respectively. The R2 value is lower than the evaluation standard of 0.5 and shows the fit of the research model in the structure model.

4.4 The effects among latent variables

After conducting an overall model test, this study further compares the effects of each potential variable in order to gain a deeper understanding of the relationship

Table 6 The effect of various latent variables in LE-AITA influence pattern

Latent variable	ICT-SE			HCIE		
	Direct	Indirect	Total effect	Direct	Indirect	Total effect
LE-AITA	0.58	0.74	1.32	0.91	-	0.91

between factors. The direct and indirect effects of each potential variable are explained as follows and appear in Table 6.

1. For the direct effect, the results of this study reveal that university students' HCIE is an important factor directly influencing their LE-AITA, and the influence effect is 0.91. A higher level of recognition of HCIE among university students implies a more significant level of LE-AITA. On the other hand, the influence effect of ICT-SE concerning LE-AITA is 0.58, indicating that university students' ICT-SE has a certain influence on their LE-AITA.
2. The indirect effect of university students' ICT-SE affecting their LE-AITA is 0.74, and the total effect is 1.32. Therefore, the impact of university students' ICT-SE influences their LE-AITA mainly through their awareness of HCIE.

4.5 Model verification results

The empirical results of university students' LE-AITA are shown in Figure 1 and are analyzed as follows. (1) The estimated value of the direct influence parameter

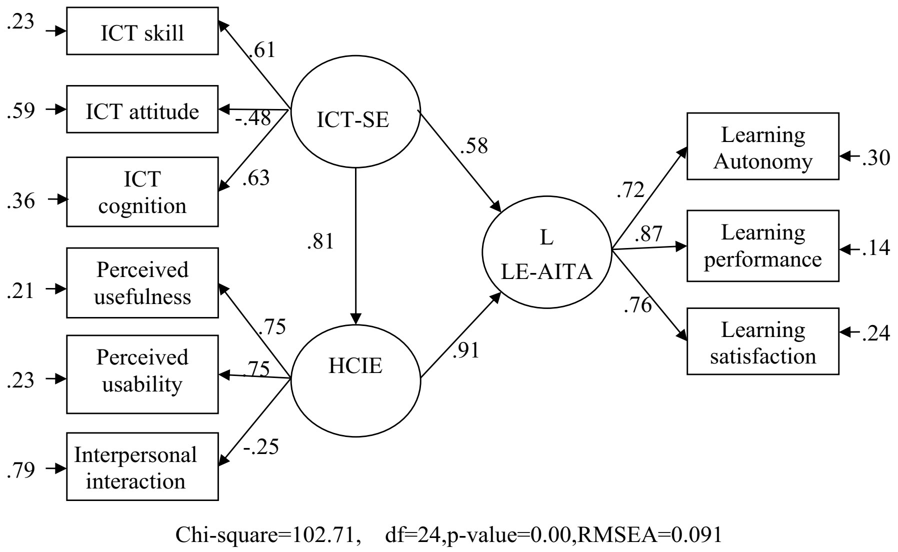

Fig. 1 Path diagram of students' LE-AAIT and its influencing factors

between ICT-SE and HCIE is 0.81 (t=15.82, $p<.05$). This means that ICT-SE has a significant effect on HCIE. (2) The estimated value of the direct influence parameters of HCIE and LE-AITA is 0.91 (t=31.78, $p<.05$). This means HCIE has a significant effect on LE-AITA. (3) The estimated value of the direct influence parameters of ICT-SE and LE-AITA is 0.58 (t=10.33, $p<.05$). This means ICT-SE has a significant effect on LE-AITA. In summary, ICT-SE, HCIE, and LE-AITA have a positive relationship.

5 Discussion

This study found that the human-computer interaction experience significantly and positively relates to the learning effectiveness of AI-based technology applications, and that students' ICT self-efficacy has an indirect correlation with the learning effectiveness of AI-based technology application through the human-computer interaction experience. The influence pattern and empirical data for ICT self-efficacy and the human-computer interaction experience on learning effectiveness of AI-based technology application exhibit a good fit.

From the perspective of the Planning Behavior Theory, it is important that establish students' ICT-SE, strengthen students' problem-solving skills, integrate information and extend knowledge through digital interfaces, by combining the Internet and multimedia teaching materials in learning content and enhancing students' learning motivation (Alahakoon & Somaratne, 2020; Al-Said & Al-Said, 2020). Teachers can use AI-based education and teaching platforms to instruct students' ICT-SE and to improve LE-AITA. "Amason Alexa Echo" is a teaching platform that can be used to teach English and other languages, and "I-Reading" is a platform with individual differential learning function levels to guide reading and math learning of adaptive reading and math software (Lopatovska, 2019; Zhou, 2019; Zhu, 2019). Students use mobile devices such as tablet PCs, smartphones, pocket PCs, notebooks or any other electronic learning activities that have assistive devices with digital information content in order to enhance learning efficiency and achievement and to achieve the best results of AI information technology learning. Therefore, enhancing students' HCIE has a better effect on enhancing LE-AITA (Ehrenbrink & Möller, 2018; Mlambo et al., 2020).

The results further show that human-computer interaction experience acts as a mediator that enhances the learning effectiveness of AI-based technology applications. Students' human-computer interaction experience mainly affects the AI application through a potential factor of information technology in learning effectiveness, among which "perceived usefulness" has a greater impact on the learning effectiveness of AI-based technology application, while "perceived usefulness" and "perceived usability" are more important for learning effectiveness of AI-based technology application.

From the viewpoint of TAM, it can be seen that university students' LE-AITA presents "perceived usefulness" and "perceived usability" as the most important considerations (Ehrenbrink & Möller, 2018; Gopal et al., 2021). Promoting the technical and modernized construction of the education curriculum in colleges and universities is crucial for enhancing higher education's science and performance (Ahn & Clegg, 2017; Che et al., 2021). It is important for teachers that a key feature of HCI and education work is to marry design processes with relevant learning theories that can inform richer designs of learning technology (Ahn & Clegg, 2017). Therefore, it is recommended that teachers apply AI information technology to professional courses and development, and they can think about how to continue to provide AI information technology operating tools and application environments to improve students' LE-AITA, such as AI translators, AI wearable watches, AI glasses, smart speakers, remote control, and AI home equipment. Che et al. (2021) proposed AI-based IoT System (AI-IoTS) wearable technology for IoT-based HCIE for college education, which has been validated based on the optimization parameter that outperforms conventional methods. Most students believe that their English level is good and hope that learning anxiety can be reduced through HCI systems (Zhou et al., 2021). Research studies noted that "perceived usefulness" and "perceived usability" were the most important factor affecting learning (Alawamleh et al., 2020; Fahimirad & Kotamjani, 2018). Therefore, when students become more recognized about HCIE, LE-AITA will relatively improve. The contribution of this research is to propose an in-depth explanation and confirmation of the importance of HCIE in LE-AITA.

University students' ICT self-efficacy also has a significantly direct effect on the learning effectiveness of AI-based technology applications. This study found a significant relationship by which students' ICT self-efficacy mainly affects their learning effectiveness of AI-based technology application through two potential factors: "ICT skill" and "ICT cognition", which have a higher impact on "learning autonomy", "learning performance", and "learning satisfaction" of learning effectiveness of AI-based technology application. Therefore, when students have more ICT skills and ICT cognition, their LE-AITA is higher.

From the viewpoint of self-directed learning theory, students should have the self-ability of "ICT skills" and "ICT cognition", manifested in the self-assessment of AI information technology, transformation of learning needs and goals, selection of efficient strategies, and the ability to collect and evaluate (Loeng, 2020; Pan, 2020). Students develop desired ICT abilities and behavior patterns in self-evaluation through self-directed learning ICT-SE with the help of the Internet and information technology. Learning resources are thus easier to obtain and can be reorganized across different fields. The needs of students and the effectiveness of learning can help achieve a student-oriented learning model. Through the evaluation of the performance of students' own behaviors or abilities, the gap between the LE-AITA model and the current performance is evaluated to evaluate their self-ability (Mlambo et al., 2020; Musharraf et al., 2018; Pillai et al., 2021).

The research findings also provided evidence that "perceived usefulness" and "perceived usability" are the main influencing factors. AI education applications for school planning have many functions. To strengthen digital education, in addition to subsidizing local governments to set up self-made education and technology centers, develop subject cross-domain courses, cultivate students' diversified learning and subject horizontal integration capabilities, and strive to improve teachers' digital teaching capabilities and prepare smart campuses, the teaching syllabus can be newly added to the field of science and technology (Al-Rahmi et al., 2021; Asthana & Hazela, 2020; Criollo et al., 2021; Hatlevik et al., 2018). To strengthen the future of automation and AI in primary and secondary education, it is becoming more important to improve teaching quality and inclusiveness in the kindergarten to the primary and secondary education system.

6 Conclusion

This study explored the relationships among university students' perceived information and communications technology self-efficacy, human-computer interaction experience, and learning effectiveness of AI-based technology applications. The results show that students' human-computer interaction experience has a significantly direct effect on the learning effectiveness of AI-based technology applications, and that ICT-SE has a significant effect on learning effectiveness of AI-based technology application through human-computer interaction experience. The influence pattern and empirical data of ICT-SE and human-computer interaction experience on the learning effectiveness of AI-based technology application present a good fit. This may indicate that the human-computer interaction experience may significantly relate to students' learning effectiveness of AI-based technology applications, which requires further investigation. Students' perception of human-computer interaction experience significantly and positively relates to the learning effectiveness of AI-based technology applications.

First, human-computer interaction experience plays an influential role, according to the study results. Moreover, schools should carry out the basic engineering of AI education applications and build an educational database, such as collecting, organizing, constructing, and storing various subjects at all levels, teaching materials, teaching plans, quizzes, exercises, student essays and voices, and other databases as well as set up test evaluation and diagnosis platforms for various subjects at all levels. The target should be the attractiveness of characters for young students, establishing online teaching system specifications, designing and building login and interactive platforms, and designing and building the system inference platform.

The application of human–computer interaction made significant contributions to new research subjects, such as multimodal physiological data analysis in hazard recognition experiments, development of intuitive devices and sensors, and the human–computer interaction safety management platform based on big data (Wang et al., 2021). The infrastructure upgrade and or enhancement base on these research findings on HCIE in Taiwan. First. From elementary schools, middle schools, universities and adults participated different themes of the "Hackathon (黑客松)" competition. Students' CIT results that are easy to use and meet the needs of human experience have been created through the Hackathon contest spirit of participants in the short time and through the process of intensive thinking and design. Second, students develop mobile devices, AR, VR, MR, and XR works in different disciplines through the "independent study (special topic) " course. The AR, VR, MR, and XR have been gradually applied to primary and secondary school AI in ICT teaching from corporate education training and university teaching. Third, it can be an important way and environment to enable students, teachers, and experts to obtain rich resources from the Internet, including electronic conference systems, virtual classrooms, tutor systems, and collaborative support that Computer-Supported Collaborative Work (CSCW) through collaborative learning in the remote education network environment. Therefore, HCIE combines multiple tactile feedback in the field of human-computer interaction and applies in the design of immersive experience and teaching aids. Students use AoEs to enhance the portal immersive experience and integrate multiple tactile feedback. Through the combination of multiple feedback devices, they can simulate the feelings of various natural environments. 4D movies are combined with " programmable tactile feedback module for large installations" and Google Cloud Vision react to the environment changes of the movie scene in real time, give users in VR virtual movies, appropriate tactile feedback experience, enhance the usability of students, and improve students' attitudes towards the perceived usefulness, perceived usability, and interpersonal interaction.

Second, university students' ICT-SE has a significantly direct effect on LE-AITA. From the viewpoint of self-adjusted learning, autonomous learning will become the mainstream learning style in the future. Students can face the trend of AI information technology smoothly, and educators urgently need to cultivate the ability to use technology and cultivate students who can adapt to future technology. Intelligent Virtual Reality (IVR) is used to attract and guide students in real virtual reality and game-based learning environments. The virtual agents can act as teachers, facilitators, or students' companions in virtual or remote laboratories. AIEd can be built into learning activities to continuously analyze student performance instead of stopping and testing. The algorithms have been used to predict, with high accuracy, the probability of students failing to complete homework or dropping out.

Third, the impact model of university student ICT-SE and HCIE on LE-AITA exhibits a good fit. The influence effects of ICT-SE, HCIE, and LE-AITA show for university students that the influence of ICT-SE on LE-AITA is revealed mainly through their awareness of HCIE. In addition, HCIE has a direct and significant effect on LE-AITA. From the influence of ICT-SE, HCIE, and LE-AITA, we can clearly see that compared with ICT-SE, HCIE has a greater influence on LE-AITA. With regard to the rational behavior theory of TAM, it can be seen that students' perceived usefulness and usability are indeed closely related to their use behavior of LE-AITA. HCIE is an important factor to improve students' AI information technology learning motivation and ICT-SE, and students are willing to continue to cultivate their own ICT literacy and information skills, which are important for enhancing their technological adjustment ability (Brian et al., 2016). AIEd can support the formation of adaptive groups based on the learner model, promote online group interactions, or summarize discussions. Human tutors can use these discussions to guide students to achieve the goals and objectives of the course, thereby facilitating collaborative learning. The Intelligent tutoring system (ITS) can be used to simulate one-to-one personal tutoring. Based on learner models, algorithms, and neural networks, it can determine the learning path and content choices of individual students, provide cognitive support and help, and allow students to participate in the dialogue.

Last, according to the Hair et al. fitness test standard, LE-AITA and its impact model verification results show that the overall fitness of this research model can be considered to be a good fit. Among them, only the RMSEA detection value of absolute fit has a moderate fit, and the other indicators meet the detection standards. This model can be said to be within the range of acceptance. As for the detection of value-added adaptation, all indicators meet the standard. In this part, the research model has better adaptation; the indicators of simple and effective adaptation detection also meet the testing standards, and so the simple and effective adaptation also is good. On the whole, LE-AITA and its influence model constructed in this study based on theory can be said to have good adaptability to data, and most of the estimated values in its parameter estimation are significant. The individual indicators show that each of the potential variables has their own importance, but the parameter value is not high, which means that the empirical data cannot have good explanatory power based on the theoretical model.

6.1 Implication

The research findings have important practical implications. The first contribution of this study is measuring ICT-SE of university students that will affect LE-AITA. The AI technology mainly provides learners with opportunities for personalized learning of their own preferences, interests, pace, and strength items. Teachers can follow the unique learning path of students and change the e-learning mode to enhance students' LE-AITA. The AI information technology has special teaching potential, and so teachers can help students visualize problems and solutions and record the path of their progress. It is important to upgrade school curricula and improve digital and STEM skills requirements. Students also need to develop the critical thinking, communication, self-awareness and management, entrepreneurial spirit, cooperation, and social skills needed in the future labor market. The school curriculum can provide education with programming and robotics, such as the "Wooden Robot" educational and entertainment toys of "Cubetto", which are equipped with modular puzzles, maps, storybooks, and wooden modules representing different commands through storybooks. In the description, the students control the robot by combining different modules on the puzzle board to make it appear in different locations on the map and the story description. Students can complete actions in the "Creation" robot by composing their own stories and experience an enlightenment education in which they learn programming while playing games (Holstein et al., 2019).

The second contribution is measuring ICT skills, ICT attitudes, and ICT cognition of university students' ICT-SE, which are important factors that affect the perceived usefulness and perceived usability of the human-machine interface experience. Schools can support and encourage the use of ICT through ICT education and training and cultivate students' skills in the information age, such as computer operations and network applications. It is important to provide a suitable platform for the use and development of educational technology in Taiwan so as to improve the AI learning environment. Taiwan's Ministry of Education has built the "Adaptive-Learning Platform" of the teaching contents, which can be extended to high school and university levels. The Adaptive-Learning Platform use as a tool and offers a cross-grade longitudinal diagnosis test and remedial instruction . It is important that a longitudinal diagnostic test features the ability to search the relevant concept downward to diagnose the students' basic concepts.

The third contribution is that measuring HCIE has a significantly direct effect on LE-AITA. Teachers should provide a variety of HCIE with AI-based teaching materials and offer students personal learning so that the AI algorithms can help teachers understand students' abilities and tailor the learning content for each student. Teachers have adopted some disruptive technology such as MOOC, GradeScope, Grammar proofreading, Paid.com to correct English essays, NWEAm, and Thinkster. AI can assist teachers in providing professional growth, improving their efficiency, and presenting other aspects of support, including saving time in pre-class preparation, reducing their management burden, having more energy to interact with students and cooperating with colleagues, and providing support for their professional development.

6.2 Limitations and future research

This study has several limitations. The subjects of this research are university students, including public and private four-year daytime general universities as well as technical and vocational schools. There is a total of 148 schools. The research results do have their limitations if they are to be inferred to other levels. Exploring the relevance of the LE-AITA variables for different levels of students and the effectiveness of HCIE's learning in different subjects is worthy of more in-depth discussion.

The grading of the questionnaire in this study is based on the self-evaluation method of students. This study did not exclude samples of students under the test who were affected by the situation, attitude, emotion, and other factors at the time of answering, or who did not answer according to the actual situation. Although from past literature and theories, this research has established a research model as completely as possible; however, there may be undiscovered influencing factors, resulting in a relatively low proportion of explanations. Therefore, according to the verification results of this model, we can further study the missing or possible increase or decrease of the dimension indicators in the theory in the future or collect more complete empirical data for verification, which may improve the consistency of the verification between this model and the empirical data.

The influence lies in the test of indices and methods. By verifying the calculation of structural equations, the index value is subject to the sample size, and sometimes the index values may influence each other. When the index is far greater than or much lower than the standard value, the judgment is more accurate; when the index is close to the standard value, then one needs to consider the possible influence of an error in the missing scope of variables. Although we tried to establish a complete research model in this study based on past research and theories, there is scant research on the topic of students' LE-AITA. Future studies can include this variable and modify the model accordingly to further investigate the cause-and-effect relationship among variables as there may be undetected factors having low explanatory power or variables which have not been identified.

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Declarations

Conflict of Interest None

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