An Analysis of the Learning Experience and Impact of a Chatbot Tutor in AI Education for a Liberal Course

Authors: Hyunjin Cha[1], and Mija Oh[2]*

Affiliation: [1]Soonchunhyang University, Republic of Korea, [2]Konkuk University, Republic of Korea
*Corresponding author: skyomj@konkuk.ac.kr

Received: 14 May 2025 | **1st revision:** 28 June 2025 | **2nd revision:** 12 November 2025 | **Accepted:** 17 November 2025

APA citation for this article:
Cha, H., & Oh, M. (2025). An analysis of the learning experience and impact of a chatbot tutor in AI education for a liberal course. *Journal of Institutional Research South East Asia, 23*(3), 348-372.

ABSTRACT

This study aimed to explore the learning experience with and evaluate the effectiveness of a chatbot tutor for artificial intelligence education in a basic liberal art course for college students. Two experimental studies were conducted. The first study explored the impact of interacting with a chatbot tutor on learning fundamental AI concepts with a sample of 38 students. The second study compared the effects of video lectures on a learning management system (LMS) with the use of the chatbot tutor, involving 118 students from four different classes. The results of the first study confirmed the applicability of AI education through chatbot tutor, indicating that the chatbot was effective in supporting students' learning of AI concepts. In the second study, both AI education through video lectures on the LMS and guided by the chatbot tutor resulted in improved academic achievement. Notably, the group that received AI education using the chatbot tutor demonstrated slightly higher academic achievement compared to the video lecture group on the LMS. These findings provide practical implications for educators and institutions involved in AI education.

Keywords: The chatbot tutor, AI education, Quasi-experimental design, self-directed learning readiness, Applicability of the chatbot tutor

1. Introduction

AI (Artificial intelligence) is utilized in a number of fields including education, computer science, medical diagnostics, business, industry, media, and communication. AI technology is expected to change the structure of employment and lifestyle as a key technology for the transition to the digital age. In response, countries around the world have realized the need for AI education, and announced AI strategies and education policies. The characteristics of AI education strategies announced in various countries are based on the premise that AI education is not just for a handful or subset of people only, but a basic competency that everyone should have. Therefore, even at universities, AI should be provided at the level of undergraduate education, so that all students receive instruction on AI regardless of major. (Szczepański, 2019; Ernst et al., 2019).

From this perspective, it is not only computer science students but also general university students who are studying basic AI education within the scope of liberal arts. There is a growing interest in AI education curriculum and methodologies that facilitate the understanding of AI for non-computer science students (Burgsteiner, Kandlhofer, & Steinbauer, 2016; Sensetime, 2018). One of the teaching strategies is to apply AI tools into an AI understanding and an educational exercise. For instance, Srikant and Aggarwal (2017) suggested that students between the ages of 10 and 15 develop friend prediction programs using Microsoft Excel, which would allow them to experience how to successfully solve related problems using data science. Chung and Shamir (2020) conducted an activity to recognize video, image, sound, and text. Some of previous studies concluded that using these tools would help students to understand AI technology. Zeng (2019) suggested that such AI education or studying AI through the use of AI tools is helpful for the competency of AI Thinking, which can help improve problem-solving skills with the use of AI. Therefore, better understanding of AI through AI classes with the use of AI tools might be helpful to create diverse and innovative things. With this in mind, this study aimed to explore the impact of using chatbot tutor as an AI tool and as a new teaching method, on the effectiveness of AI education.

Chatbot is an intelligent application that converse with people through voice or text in national language (Essel et al., 2022; Vázquez Cano, Mengual Andrés & López Meneses, 2021). Recently, the usage of the chatbot is rapidly increasing in various fields (Nguyen et al., 2022). Education is one of the fields where chatbots are increasingly employed as well (Kumar, 2021). Chatbots used in education can be broadly divided into two categories; tutors and learning support tools (Holmes, Bialik, & Fadel, 2019). Chatbots as tutors assist teachers, for example, New Zealand's AI math teacher, Amy. Amy was introduced to 10 high schools in New Zealand. It informs students where they lack mathematics knowledge in the process of learning mathematics and provides customized feedback on errors in the student's problem-solving process. As a learning support tool, chatbots play an auxiliary role in education, providing answers to questions (Lin, & Chang, 2020) and materials quickly, when learners need them (Fryer & Carpenter, 2006). In addition, through analysis of the conversation between the chatbot and the learner, it can inform the instructor of the student's learning status, helping to enable customized learning support (Pérez, Daradoumis, & Puig, 2020).

It can also help student’s self-regulated learning (SRL) (Guan et al. 2024). Indeed, Guan et al.(2024) proved that educational chatbot could support productive SRL processes by analyzing a systematic review of the previous literature. However, it also found that some of chatbot use did not show statistically significant effects on students who studied computer science (Oliveira et al., 2021). Looking at the results of the meta-analysis, it is difficult to find cases where AI chatbots were applied to teach AI in liberal arts courses.

As with online learning, one of the advantages of using chatbots in education is that learners can receive education services anytime, anywhere, through smart devices, without time and space limitations. In this respect, the effectiveness of traditional online learning such as video lecture has shown similar outcomes to education provided by chatbots(Evans, 2014; Nisar, 2002; Knowles, 1975; Yu, 2021). However, there is ongoing discourse regarding the various drawbacks of asynchronous video-based learning, which has been mainly adopted in online learning of higher education contexts, especially, during COVID pandemic periods.

During the COVID-19 in higher education, asynchronous video-based lectures were uploaded to Learning Management Systems (LMS) for students to engage in self-directed learning. However, due to a lack of social presence in interactions with peers or instructors, learners experienced negative emotions such as boredom, frustration, confusion (Lee et al., 2021). Social Presence Theory (SPT) emphasizes that the isolation of asynchronous video lectures creates a vacuum of social presence, which might be critical for maintaining learning motivation and engagement (Short, Williams, & Christie, 1976; Lin & Chang, 2020). In addition, it has limited support for SDL since LMS provides the same content and sequence regardless of learner differences. The limitations of the LMS would be taken into consideration with Cognitive Load Theory (CLT), a one-size-fits-all video lecture can impose a high extraneous cognitive load on learners, forcing them to process information that may be redundant (if they already know it). It means hindering effective learning (Sweller, 1994).

In this point, chatbot might play a positive role in promoting social presence and helping students' SRL during online learning, based on the results of the previous literatures related to the use of chatbot in education. For instance, it was revealed that chatbots have educational benefits such as motivating learners by providing a sense of social presence through interaction (Lin & Chang, 2020). In addition, Okonkwo & Ade-Ibijola (2020) suggests that learners find it more convenient to engage with learning contents recommended by a chatbot, as compared with self-directly searching for relevant learning materials such as videos or resources on LMS or webpages. Furthermore, unlike the traditional video-based learning on LMS, chatbots can play a role in identifying students' individual knowledge gaps and personalizing students' pace of learning.

Finally, the chatbot tutor provides a learning enviromnet to practice at any time with autonomy based on its suggestion. It is also possible to continuously provide personalized feedback and customized responses related to the individual student.

In summary, a chatbot tutor can provide two key affordances: (1) it can optimize cognitive load by providing personalized scaffolding (e.g., pre-quizzes to diagnose knowledge, followed by targeted content), and (2) its conversational interface can simulate interaction, thereby increasing social presence. (3) it can motivate learner by providing self-determination (autonomy, competence, and relatedness).

Against this backdrop, this study aims to examine the impact of using a chatbot tutor in AI education during a basic liberal arts course for college students. Despite the growing interest in AI education for non-computer science students, limited empirical research has evaluated the instructional effectiveness of chatbot tutors within liberal arts contexts. To addresses this gap, this study systematically examines how a chatbot tutor influences both academic achievement and self-directed learning readiness in liberal arts courses for students at the undergraduate level. In addition, the study aims to compare the effects of personalized video lectures delivered through the chatbot with the traditional approach of video lectures provided on the LMS.

In sum, this study attempted to answer the following research questions:

> RQ1: To what extent does a chatbot tutor, implementing personalized scaffolding affect students' academic achievement in an introductory AI course compared to traditional LMS-based instruction?
> RQ2: What is the comparative effect of the chatbot tutor (versus an LMS) on the development of students' self-directed learning readiness (SDLR)?
> RQ3: What are the learning behaviors (e.g., interaction patterns) and perceived experiences (e.g., satisfaction, perceived autonomy) of students engaging with the chatbot tutor?

2. Theoretical Background

Self-directed Learning (SDL) and its limitation of online learning

Self-Directed Learning (SDL) is a process where individuals take the initiative in diagnosing their learning needs, formulating goals, identifying resources, and evaluating outcomes (Knowles, 1975). In typical online learning based on LMS, SDL is a crucial factor for success. However, the passive, non-interactive nature of traditional video lectures on LMS provides one-size-fits-all support, often leaving students feeling isolated and unmotivated (Lee et al., 2021; Marchand & Gutierrez, 2012).

In this respect, based on a previous research, we also tried to provide more interactive way of a learning method and customized learning paths as compared to the traditional approach of video lectures provided on LMS. One of the reasons is that the COVID-19 period has brought about discussions on issues such as difficulties in self-directed learning, lack of student engagement, and emotional challenges due to uniform learning method of the traditional video lectures (Marchand & Gutierrez, 2012).

A Theoretical Framework for the educational chatbot

An AI chatbot is an AI-based conversational software program that answers users' questions or provides relevant information through text or voice. In the early days, chatbots were mainly used in the service field, but with the recent development of machine learning technology, flexible conversations with chatbots are possible, making them useful in the education field as well (Fryer & Carpenter, 2006). In addition, learners can ask questions and get answers anytime, anywhere (Sandu & Gide, 2019), and have access to relevant learning materials (Verleger & Pembridge, 2018). By recording the conversation between the chatbot and the learner, and providing it to the teacher, the teacher can grasp which parts the learner finds difficult and what topics the learner is interested in, and furthermore, the learners can control the learning process and pace, themselves (Hamzah et al., 2021).

In the field of education, chatbots can be broadly categorized into two types: chatbot tutors and learning support tools (Holmes, Bialik, & Fadel, 2019). The chatbot tutors assist educators. For instance, a chatbot identifies areas where students lack mathematical understanding during the learning process and provides personalized feedback on their problem-solving approaches (Verleger & Pembridge, 2018). As learning support tools, chatbots serve as educational aids by promptly delivering answers to queries (Lin & Chang, 2020) and learning materials when learners require them (Fryer & Carpenter, 2006). Furthermore, by analyzing the interactions between chatbots and learners, instructors can gain insights into the students' learning progress, facilitating tailored learning support (Pérez, Daradoumis, & Puig, 2020).

Chatbots are also attractive learning tools in that they allow learners to ask questions in learning problem situations where they do not want to show their fellow learners what they don't understand, differently from the face-to-face education contexts. Chang, Kuo, & Hwang (2022) discussed that it was possible to acquire knowledge and increase the interactivity of learning by repeatedly solving quizzes through chatbots. Essel et al. (2022) also proved that using a chatbot makes learning interesting and improves class adaptability. Chang et al.(2022) and Essel et al.(2022) also proved that chatbot tutors helped improve students' academic achievement. Furthermore, Hamzah et al. (2021) conducted experiments by allowing chatbots to be used as self-learning assistants and found that chatbots are useful in bridging the skills and education gap. Previous studies using chatbots for education showed that chatbots were used in various ways. What these preceding studies have in common is that pedagogical use of AI chatbots could bring about a shift in educational theory, where learning traditionally takes place in a learning situation designed by a teacher, to one in which the learning experience is determined by the learner (Al-Abdullatif, Al-Dokhny, & Drwish, 2023). This change has many positive effects.

To understand the differential impact and positive effects of the chatbot tutor, we adopt a theoretical framework, integrating Cognitive Load Theory (CLT), Social Presence Theory (SPT), and Self-Determination Theory (SDT).

a. Cognitive Load Theory (CLT) and Personalized Scaffolding

CLT suggests that instructional design should consider three types of load: intrinsic (task complexity), extraneous (poor instruction), and germane (schema formation) (Sweller, 1994). A traditional video lecture on LMS imposes the same load on all students, creating a high extraneous load for those who already know the content (redundancy) or for those who are lost (lack of scaffolding). In this study, the chatbot tutor can support this cognitive load. By diagnosing student's pre-knowledge through the pre-quiz, the learner can skip the video, effectively removing the extraneous load. If they answer incorrectly, the chatbot tutor recommends the video lecture as necessary scaffolding, directing the learner's cognitive resources toward germane load (i.e., actual learning).

b. Social Presence Theory (SPT) and the Conversational Interface

One of the main characteristics of the chatbot tutor is conversational interface. Its interaction style, characterized by turn-taking, greetings, and encouragement, provides a sense of presence. SPT defines the perceived social presence in mediated communication (Short et al., 1976). Previous studies proved that a high degree of social presence is linked to increased motivation, engagement, and satisfaction (Lin & Chang, 2020). One of the weaknesses of asynchronous video lecture on LMS is the lack of social presence, leading to feelings of isolation and decreasing maintained motivation (Lee et al., 2021).

Indeed, learning can be motivated by providing a sense of social presence through interaction. Lin & Chang (2020) have stated that because chatbots talk like humans, learners get the feeling that the other person exists, and that the other person's presence alone helps motivate learning. In addition, interaction occurs through conversation with the chatbot, which has a positive effect on academic achievement, satisfaction, and learning interest (Kim & Lee, 2019).

c. Self-Determination Theory (SDT) and promoting learner's motivation

SDT provides a systematic theory of human motivation (Ryan & Deci, 2000), which suggests that intrinsic motivation increases when three basic psychological needs (autonomy, competence, and relatedness) are met. In SDT, autonomy means that the need to feel a sense of choice and control over learner's actions, and competence means that the need to feel effective and master challenges. Finally, relatedness is about the need to feel connected to others.

In this perspective, chatbot tutor might provide three aspects: autonomy, competence, and relatedness. To explain, chatbot tutor provides an opportunity to practice at any time with its suggestions. Chatbots can send and receive conversations whenever learners want, through a smart device (Fryer & Carpenter, 2006). It is also possible to continuously provide personalized feedback. Chatbots can continuously answer questions from learners without tiring (Fryer & Carpenter, 2006) and provide different answers appropriate to the question (Chen, Vicki, & Sutrisno, 2020). It can influence learner's motivation and satisfaction.

Therefore, we conceptualize the chatbot as a learning environment that supports these fundamental theoretical perspectives, leading to more self-determined, motivated, and more successful learning. Therefore, we seek to explore the benefits that the use of chatbot in the similar contexts offer in contrast to the conventional methods of video-based instruction. The following figure 1 shows the conceptual map of the impact of chatbot tutor which will be explored at the small-scale empirical studies in this research.

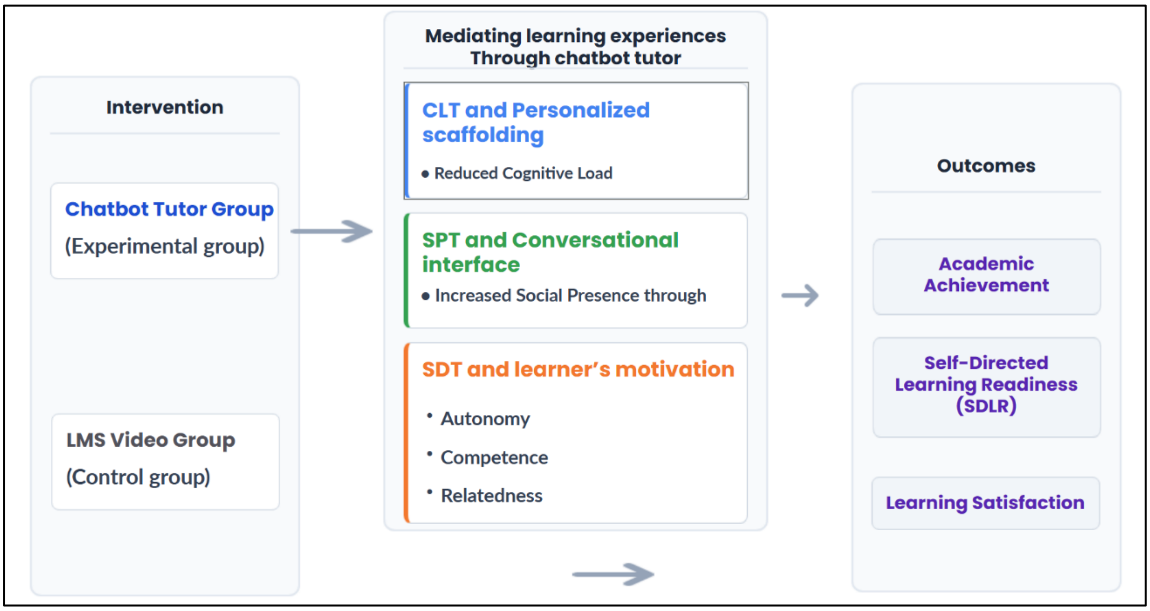

Figure 1: A conceptual map of the impact of chatbot tutor

3. The chatbot tutor for AI education

In this study, the chatbot that plays the role of a tutor who diagnoses knowledge and guides or recommends learning based on the student's knowledge level in a specific area, while simultaneously interacting with students, is defined as a chatbot tutor. In this study, the chatbot tutor, unlike generative AI-based chatbots such as Chatgpt, had limited freedom, while allowing students to do supplementary learning in a structured flow. A chatbot tutor was developed to provide college students in AI education within a fundamental liberal arts course with more customized instruction. The chatbot tutor was designed to consist of five modules on AI based on previous studies and books related to the AI curriculum. The chatbot tutor was implemented based on a scenario in which the student can learn each lesson by talking to the chatbot.

The chatbot was built on the frogue.danbee.ai platform and the chatbot tutor used in this study was designed as a 'scenario-based, rules-based' system, not based on natural language processing (NLP) or generative AI. In this study, 'personalization' does not mean NLP-based adaptive personalization, but 'structured customization' that suggests different learning paths to each learner based on the pre-quiz results and learner's learning motivation. This is because it is a structured experiment to enable students to use chatbots in a consistent way to evaluate and learn about AI, and it was developed for the purpose of comparing LMS video footage with methodological aspects rather than content aspects.

The following figure 2 shows a sample screen of the chatbot.

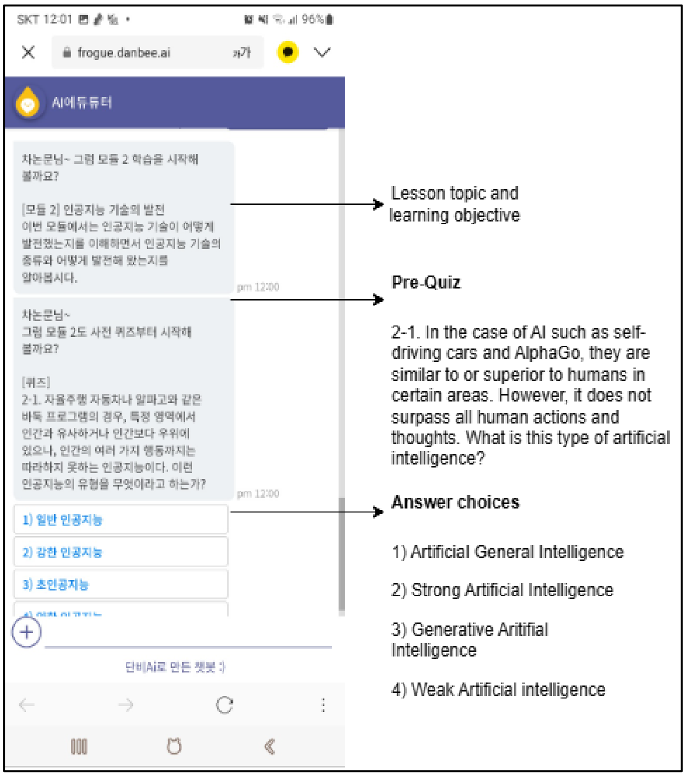

Figure 2: A Screenshot for the Chatbot Tutor

When a student starts to have a conversation with the chatbot tutor, it presents a learning objective with the lesson topic and utilizes the question-and-answer methods in order to identify whether the student has knowledge relevant to the lesson (Ng et al., 2021). First of all, a pre-quiz is given. Based on the student's performance in the pre-quiz, the chatbot tutor provides personalized instruction. If the answer is incorrect, the chatbot encourages the student to delve into the target knowledge by offering a video lecture. Whether students listen to the lecture or not, a post-quiz is administered to assess the student's learning progress and determine readiness to proceed to the next lesson. In case the student performs poorly in the post-quiz, the chatbot recommends revisiting the lecture for further comprehension. Throughout the learning process, the chatbot tutor accommodates individual learning paces, allowing students to study AI at their preferred speed.

4. Methodology

Research design and procedure

Building upon the conceptual framework and review of prior studies, this study consists of two different studies, to empirically assess the chatbot tutor's educational impact. The first study was conducted to explore the impact for college students enrolled in an AI education course as part of a fundamental liberal arts curriculum, of interacting with a real chatbot tutor. The name of the lecture in the first study is 'Computational thinking and AI' which is a compulsory liberal arts course for first-year students at one of the universities located in the capital of Korea. This lecture was included to learn the concept of the chatbot in order to understand how it works as one of the AI technologies and to participate in a chatbot implementation exercise such as for a pizza order chatbot using dialog flow. After learning the concept of the chatbot and implementing the chatbot using dialog flow, they were asked to study AI by interacting with the chatbot tutor. To measure the effects of the chatbot tutor, the achievement tests and the self-directed learning readiness (SDLR) questionnaires were taken before and after interacting with the chatbot. Then, questions on the level of satisfaction with chatbot use in AI education, was completed at the end of the course.

Table 1: Experimental procedure in the first study

Schedule	Contents	Instructional methods
9.13 (week 3)	The concept of chatbot	Offline class, Theory
9.20 (Week 4)	- A chatbot implementation practice such as a pizza order chatbot using dialog flow - Pre-test/ Pre-questionnaire about SDLRS	Offline class, Practice
	AI in our daily life	Online
9.27 (Week 5)	Advances in AI technology	Online
10.4 (Week 6)	AI technology and data science	Online
10.11 (Week 7)	Principles and applications of machine learning among AI technologies	Online
10.18 (Week 8)	AI and ethics	Online
10.25 (Week 9)	Post-test/ Post-questionnaire about SDLRS, Satisfaction questionnaire	Offline

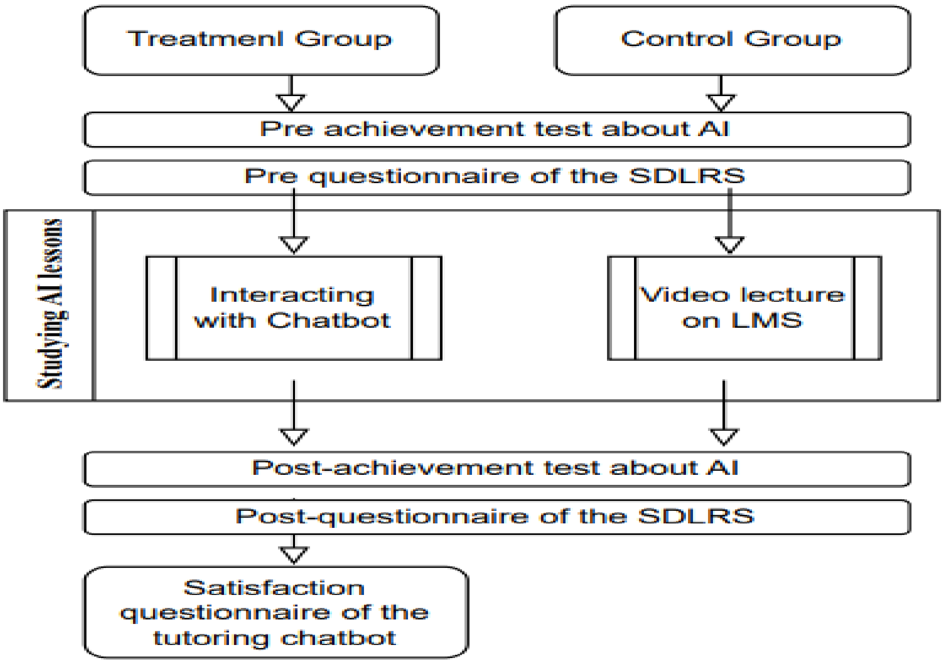

Figure 3: Experimental Procedure in the Second Study

The second study aimed to compare the effects of traditional asynchronous video lectures on a LMS with video lectures delivered through the chatbot tutor. The study was conducted in a mandatory liberal arts course for first-year students at universities located in a small and medium-sized city in Korea. Two out of four classes were assigned as the experimental group, which interacted with the chatbot tutor to study AI, while the remaining two classes served as the control group, utilizing e-learning methods for AI instruction. Both groups were asked to take a pre-test about AI and complete a pre-questionnaire about their SDLR, before studying and then they were asked to take the AI lessons wherever and whenever they wanted during the next three weeks. As described above, same video lectures were utilized in LMS and AI chatbot tutor. To ensure treatment fidelity, the chatbot tutor delivered identical instructional sequences for all learners, with adaptivity only based on quiz result. Interaction logs were collected automatically and the learner's quiz results in each module were recorded with time. The quiz results showed the number of retry attempts per quiz. These logs were analyzed descriptively to confirm that interaction patterns aligned with the intended instructional design and to observe variation in self-paced learning among learners. The interaction logs in the experimental group utilized the chatbot tutor for self-directed AI study demonstrated the consistency and fidelity of the instructional design led by chatbot tutor, whereas the log of LMS in the control group exclusively relied on the LMS for all lectures demonstrated the consistency and fidelity of the instructional design led by video lectures.

After three weeks, both groups took a post-test and completed the post-questionnaire about their self-directed learning readiness. The experimental groups only, were asked to fill in a learning satisfaction questionnaire about the chatbot to measure how they felt about their interactions. The following table 2 shows the variables integrating in this study.

Table 2: Variables and operational definition for the research tools

Variable	Operational Definition	Research Tool	Reference
Self-Directed Learning Readiness (SDLR)	A competency that enables the students to decide their own learning needs, including independence, preparation to learn and motivation	SDLRS (25 items, 5-point Likert scale)	Guglielmino (1977, 1978)
Academic Achievement	Understanding and applying AI knowledge and ethics	Pre-/post-tests on AI concepts	Ng et al., (2021)
Learning Satisfaction	Learners' satisfaction with chatbot interaction and AI learning experience	Satisfaction survey (5-point Likert scale)	

Participation selection

Thirty eight students from a university in the capital of Korea participated in the first study. The sample size was considered sufficient based on Cohen (1988)'s power analysis assuming a medium effect size ($d = 0.5$), $\alpha = 0.05$, and power $= 0.80$ for a paired t-test typically require a sample size of approximately 34 participants. The course in the first study is a basic liberal arts course that all first-year students must take. In particular, this curriculum was designed to cultivate basic knowledge about computational thinking and AI, for humanities students. Therefore, the 38 students had backgrounds that encompassed various majors. Table 3 and Table 4 shows the profiles of the particiapants in the first study.

In the second study, 57 students in two classes where a total number of students are 82 were in the treatment group who voluntarily participated and completed the study of AI by interacting with the chatbot tutor, and 61 students from 2 different classes where a total number of students are 82 were in the control group who agreed to participate and completed the study of AI through video lecture on LMS. All four classes are designed with the same curriculum as a basic liberal arts course that all first-year students must take.

Table 3: Major profile of participants in the first study

Major	N	Percent
Business	17	44.7
Education	2	5.3
Social Science	10	26.3
Art & Design	9	23.7
Total	38	100

Table 4: Gender profile of the first study

Gender	N	Percent
Male	13	34.2
Female	25	65.8
Total	38	100

Instruments

Video clips that were designed and developed by an instructor for the basic AI education, were utilized for both the AI chatbot tutor and in the e-learning. In other words, the content was the same, but the delivery and teaching methods were different.

Self-directed learning readiness (SDLR) is considered a competency that enables the students to decide their own learning needs, including independence, preparation to learn and motivation (Dogham et al., 2022). Wong et al. (2021) emphasized that SDLR is a professional as well as necessary, competency to be developed by students since it helps them to monitor and assess themselves during their learning. In this study, the self-directed learning readiness scale (SDLRS) proposed by Guglielmino (1977, 1978) with the 5-point Likert scale was adopted and adapted according to the purpose and the context of the study. The total number of items in the SDLRS is 25. An example of an SDLRS item is 'I think I am entirely responsible for my studies'. The SDLRS suggested by Guglielmino (1978) is an eight-factor structure model including (a) four items in the Self-concept as an effective learner, (b) eight items in the Openness to learning opportunities, (c) four items in the Initiative and independence in learning, (d) three items in the Accepting of responsibility for one's own learning, (e) two items in the Love of learning, (f) three items in Creativity, (g) three items in the Ability to use basic study skills and problem solving skills, and (h) two items in the Positive orientation to the future. Of these eight factors, creativity and initiative and independence factors were deleted in this study, and one item from self-concept and one item from openness were deleted.

To validate the factor structure of the Self-Directed Learning Readiness (SDLR) scale, an exploratory factor analysis (EFA) was conducted using 17 items. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy yielded a value of .784, demonstrating a meritorious level of sampling sufficiency for factor extraction, and Bartlett's test of sphericity was significant ($p < .001$), indicating that the correlation matrix was factorable. Communalities ranged from .602 to .846, with the majority exceeding the recommended threshold of .60, confirming that the items were robustly accounted for by the common factor. Although the scale was conceptually designed to represent six subdimensions of SDLR— self-concept, openness, accepting of responsibility, love of learning, problem solving skills and orientation to the future—the EFA results did not support a clear multidimensional structure. This finding suggests that SDLR may manifest as a holistic and integrated construct rather than a set of discrete dimensions among learners. Accordingly, the current study operationalized SDLR as a unidimensional construct comprising 17 items to enhance parsimony and conceptual coherence. The internal consistency of the unified 17-item SDLR scale was satisfactory, with a Cronbach's alpha of .79.

The satisfaction questionnaire focused on how students interacted with the chatbot, whether they studied the learning contents when they answered the given quiz correctly, since the chatbot tutor offered the choice on whether or not to reinforce learning, and how they felt while they were interacting with the chatbot, the effects of the chatbot, and so on. The questions about how they interacted or why they acted with the chatbot were designed as multiple-choice questions and questions related to the satisfaction of the chatbot were designed as 5-points of a Likert scale.

Analysis of the data

In the first study, a paired sample t-test analysis was conducted for the pre-post achievement tests and the pre/post SDRLS. Statistical analysis of the data were performed using SPSS 21.0. In the second study, a mixed-methods approach was adopted to compare the effects on achievement and the self-directed learning readiness competency, of the instructional methods offered by the chatbot tutor and LMS.

To complement the limitations of intact class assignment rather than random assignment, an independent samples t-test was conducted between the two groups on the pre-test scores (academic achievement, SDLR) before the experimental treatment to verify initial homogeneity. To mitigate potential pre-group differences, pre-test achievement and SDLR scores were used as covariates in subsequent ANCOVA analyses.

Pre-group equivalence tests confirmed no statistically significant baseline differences between groups. Then, one-way ANCOVA was performed to compare the differences in academic achievement and the SDRLS before and after the program with the chatbot tutor and LMS, using pre-score as the covariate and post-score as the dependent variable. To mitigate the influence of initial group differences, ANCOVA was employed using the pre-test scores as covariates. In the satisfaction questionnaire, descriptive analyses including frequencies, percentages, means, and standard deviations were performed. The effect size was analyzed based on Cohen's d (Cohen, 1988).

5. Results

Academic Achievements

In the first study, it was revealed that the chatbot tutor had a positive influence on academic achievement. As shown in the table 5, the result of the paired sample t-test proved that the achievement scores in the post-test were improved by a statistically significant amount ($t=-3.075$, $p<0.05$). The Cohen's effect size is 0.734, which means that the effect size is quite large.

Table 5: Result of the Paired Sample t-test in Academic Achievement Measurement of the First Study

Measure	Pre-test (N=38)		Post-test (N=38)		difference	t	effect size (Cohen's d)
	M	SD	M	SD			
Achievement	4.39	1.569	5.53	1.538	1.132	-3.075**	0.734

*p<.05, **p<.01, ***p<.001

In the second study, a paired sample t-test analysis in both groups revealed statistically significant differences between the pre and the post achievement test as shown in the Table 6. This means that learning AI through either the chatbot tutor approach ($t= -8.034$, $p<0.001$) or by LMS ($t= -3.684$, $p<0.001$) is effective in terms of academic performance. However, the effect size is larger by chatbot interactions (Cohen's $d = 1.146$) than study through LMS (Cohen's $d = 0.542$).

Table 6: Result of the Paired Sample t-test in Academic Achievement Measurement of the Second Study

Measure of achievement	Pre-test		Post-test		difference	t	effect size (Cohen's d)
	M	SD	M	SD			
chatbot group (N= 72)	3.72	1.258	5.39	1.632	-1.667	-8.034***	1.146
LMS group (N= 75)	3.96	1.728	4.87	1.630	-0.907	-3.683***	0.542

*p<.05, **p<.01, ***p<.001

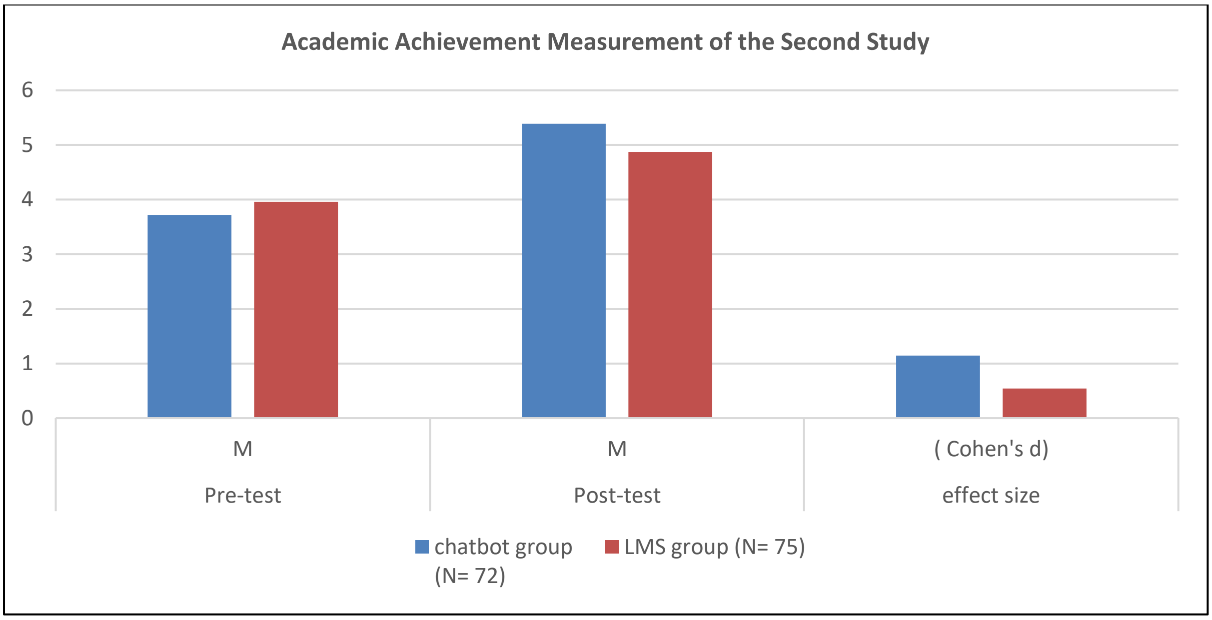

Figure 4: Comparison of academic achievement measurement of the second study

The one-way ANCOVA analysis that was performed to compare the changes in the achievement by both the experimental and control groups showed a significant difference. The result in Table 7 shows that learning method (group) is the main effect in influencing changes in achievement (F=4.838, p<0.05), indicating that students who studied AI by interacting with a chatbot tutor (treatment group) had a better, and statistically significant, achievement difference than those who studied AI through LMS.

Table 7: Results of the One-Way ANCOVA between Two Groups in Academic Achievement of the Second Study

Measure	Pre-test (N=38)		Post-test (N=38)		Change	t	effect size (Cohen's d)
	M	SD	M	SD			
SDLRS	3.54	0.381	3.85	0.385	0.314	-3.684***	0.809

*p<.05, **p<.01, ***p<.001

Self-directed Learning Readiness

In terms of self-directed learning readiness (SDLR) competence, from the first study, it was also proved that students could improve this competency by studying AI with the use of the chatbot tutor. As shown in table 8, the result of the paired sample t-test proved that the change in SDLRS between pre and post-questionnaires was statistically significant (t=-3.684, p<0.001) with a large effect size (the Cohen's d = 0.809).

Table 8: Result of the Paired Sample t-test in SDLRS Measurements of the First Study

Measure	Pre-test	Post-test	Change	t	effect size

	(N=38)		(N=38)				(Cohen's d)
	M	SD	M	SD			
SDLRS	3.54	0.381	3.85	0.385	0.314	-3.684***	0.809

*p<.05, **p<.01, ***p<.001

In the second study, a paired sample t-test analysis was conducted. The treatment group (chatbot tutor) showed statistically significant differences in the SDLRS. This can be interpreted as, learning with a chatbot tutor may help students to improve SDLR (t= -2.115, p<0.05). However, the effect size is small (Cohen's d = 0.3) as shown in the Table 9. In the LMS group, there was no significant difference in the SDLRS.

Table 9: Result of the Paired Sample t-test in SDRLS Measurement of the Second Study

Measure of achievement		Pre-test		Post-test		Change	t	effect size (Cohen's d)
		M	SD	M	SD			
SDLRS	chatbot group (N= 56)	3.5336	0.37487	3.6481	0.38962	-0.11450	-2.115*	0.3
	LMS group (N= 61)	3.5391	0.3851	3.6528	0.5005	-0.11379	-1.911	0.25

*p<.05, **p<.01, ***p<.001

For comparison of the two teaching methods, the one-way ANCOVA analysis revealed that there was no statistically significant difference in the treatment and control groups in terms of SDLRS as shown in Table 10.

Table 10: Result of the one-way ANCOVA between Two Groups in SDRLS of the Second Study

Source		SS	Df	MS	F
SDLRS	Mean of Pre-SDLRS	1.429	1	1.429	10.124**
	Main effect (Group)	.000	1	.000	.002
	Error	16.088	114	.141	
	Total		117		

*p<.05, **p<.01, ***p<.001

Although the chatbot group demonstrated within-group improvement in SDLRS, the ANCOVA comparison did not reveal a significant difference between the chatbot and LMS groups. That is, the chatbot group showed statistically significant within-group improvements in SDLR scores after three weeks of experimental treatment (Table 7). However, in an ANCOVA analysis comparing the two groups with the LMS group (Table 8), the difference in post-test scores between the two groups was not statistically significant. This suggests that the self-directed learning behaviors required in both conditions were already comparable, given that both formats allowed students to regulate their learning pace and time autonomously. Additionally, SDLRS reflects more continued motivation and metacognition, which may require longer instructional duration or sustained feedback cycles to change meaningfully.

Satisfaction

The satisfaction questionnaire was applied identically to both studies to analyze the chatbot tutor usage pattern, and satisfaction. The questionnaire was conducted anonymously and voluntarily. Therefore, the two datasets from both the first and second studies were merged and analyzed together as shown in Table 11.

Regarding satisfaction with the use of the chatbot tutor, students were most satisfied with the convenience of being able to study anytime, anywhere (M=4.11, SD=0.795). From the open-ended question, a student (S58) responded, “it was nice to be able to do it wherever and whenever I wanted, and to be able to review parts I didn't know over and over again”. Another student (S100) said that it was comfortable because there were no restrictions on space or time.

A student thought it was meaningful to learn AI-related topics through chatbots incorporating AI technology (M=3.98, SD=0.689), saying that the use of artificial intelligence in the process of learning artificial intelligence is a very new approach.

Moreover, in terms of the chatbot as an educational platform, most students said that it would be useful to use chatbots as learning tools in the future (M=3.94, SD=0.806).

However, some students felt it was distracting to study through chatbots (M=2.5, SD=0.993). Furthermore, quite a few students responded that there is a negative aspect to not learning regardless of the level of knowledge they currently have, if the quiz presented by the chatbot was answered correctly (M=3.32, SD=1.007). A student (S20) reflected, “it was nice that I could choose the parts I needed and study more, but I also felt like I didn't have to listen to them, which was a bit disappointing”.

Table 11: Analysis of satisfaction from use of the tutoring chatbot

Satisfaction with the use of the tutoring chatbot (N=103)	**M**	**SD**
Learning while talking to a chatbot is **fun**	3.4	0.984
Convenient because I can learn at the time and place I want with the chatbot.	4.11	0.795
Effective to check what I know and what I don't know and provide customized learning.	3.85	0.767
Learning through chatbots is **distracting**	2.5	0.993
Existing learning methods (offline, e-learning, etc.) are **more effective than chatbots.**	3.4	0.957
If the quiz presented by the chatbot is answered correctly, there is a **negative aspect of not learning regardless of the level of knowledge I currently have.**	3.32	1.007
More effective if the chatbot is developed more intelligently.	3.68	1.118
Meaningful to learn AI-related topics through chatbots incorporating AI	3.98	0.689

technology.		
Useful to use chatbots as learning tools in the future.	3.94	0.806
Willingness to participate again if another opportunity to learn using chatbot is given.	3.83	0.809

From analyzing comments provided about the chatbot tutor, some students said that it was interesting because it was the first experience of a new teaching method, and depending on my answer, the tutoring chatbot gave me a different response, but many students mentioned that chatbot tutors should be more intelligent. Students (S82, S84) discussed that they think it was a little more interesting because it was a system with different manuals for each situation, rather than a system that always provided the same answer.

6. Conclusion

Discussion

This study aimed to explore how good the learning experience provided by a chatbot tutor could be when provided to university students studying AI in a basic liberal arts course. The results of this research from two separate studies confirmed the applicability of using a chatbot tutor. Firstly, both studies proved that learning about AI with the use of the chatbot tutor was effective. This is a similar result to that seen with other previous studies such as those of Kim & Lee (2019) and Crown et al. (2011). These results are consistent with Alokyan et al.'s (2024) meta-analysis of 27 studies on chatbots, which again shows that chatbots can have a positive effect on self-directed learning (SDLRS). However, this study specifically aimed to compare the impact of using LMS on self-directed learning.

In this regards, more interestingly, the second study from this investigation proved that academic performance was statistically better than studying the same curriculum through LMS. In terms of educational methods, the video-based lecture on LMS and the chatbot tutors have similarities in that learning is possible anytime, anywhere and at the places and times the learner chooses. In the second study, based on the advantages of the use of LMS and the chatbot tutors, students were allowed to learn AI at times and places they wanted. The only difference was that education was provided either by interacting with the chatbot tutor or by LMS for themselves. One of the differences between the two was that in the LMS group, students were required to study all given content. However, in the chatbot group, students could decide whether or not they wanted to study particular parts based on whether or not they answered the quizzes correctly. In the end, students in the chatbot group may not have studied all five lessons, but they did have a statistically better increase in achievement than those of the LMS group. This can be seen as a result similar to that of Hamzah et al. (2021) who used the chatbot as a self-study assistant in bridging the skills and education gap. From this finding, it appears that students do not have to study all content to achieve the learning objective, but that it might be more effective allowing them to decide whether to study on their own level in a self-directed way and then learn the necessary parts more effectively.

This result can be reflected from the CLT. From the CLT perspective, forcing unnecessary explanations (such as the entire LMS video) on learners who already know the content actually hinders learning by creating an extrinsic cognitive load. Chatbots might maximize learning efficiency by eliminating this redundancy. Ultimately, the fact that the chatbot group showed higher performance despite skipping the content can be explained by the Expertise Reversal Effect of cognitive load theory (Kalyuga et al., 2003). Moreover, from the SDT perspective, the choice of deciding to skip a video is a significant metacognitive activity. While the LMS group passively watched the video, the chatbot group independently assessed their own level by understanding themselves and actively customize their learning path. This suggests that their learning engagement might be more intrinsic and motivated by choosing their own choice with autonomy than mere exposure time to the content.

From this result, the chatbot tutor might help students to study in a self-directed way. In addition, this study showed that there was a positive effect in terms of improving students' self-directed learning readiness as a competency, by an appreciation of their own level and thus having self-directedness in their learning. However, in comparing the effects of the video lecture on LMS with through the chatbot tutor, there was not a statistically significant difference. From previous studies related to e-learning or flipped learning, online learning methods might positively affect self-directed learning readiness (Khodaei et al. 2022). Student's self-directed learning readiness is closely related to e-learning (Chau, et al. 2021), since the online learning contents provide students with greater flexibility and force students to adopt SDL. Interestingly, Al-Adwan et al. (2019) found that self-directed learning negatively affected student's satisfaction and continued usage intention. Indeed, this greater flexibility and SDL are required of students in both the video lecture on LMS and through chatbot approaches investigated here and hence might be a reason for the lack of a significant difference in the comparison of the two groups.

In addition, the positive results of this study may be related to the high digital literacy of the Korean university students (participants in this study) and the familiarity of the mobile learning environment (OECDb, 2023). For students with low digital literacy (novice in Kalyuga et al., 2003), the autonomy of chatbots may not have positive effects. Therefore, for students with low digital literacy or SDL, the skip option provided by chatbots can actually lead to neglect or learning loss. Therefore, future study might be conducted to compare two different students groups in order to generalize the results of this study to other cultural backgrounds.

In particular, with the recent technological advancements in LLM, many attempts are being made to integrate chatbots with LMS to support students' learning. Sedrakyan et al. (2024) also investigated the positive effects and concerns of integrating chatbots into LMSs among instructors and students in higher education. The results presented in this study show that when chatbots are effectively integrated into LMS in the future, the advantages of two methods need to be effectively integrated rather than just one specific method.

The following Table 12 shows how the research questions are aligned with literature findings, methodological steps, and analytical outcomes.

Table 12: A mapping table of research questions and findings based on the theoretical foundations

Research Objective	**Literature finding**	**Methodology**	**Outcome in this study**
Evaluate chatbot tutor's effectiveness in AI learning	Chatbot systems help improve student's academic achievement (Chang et al.(2022); Essel et al.(2022)) and personalized scaffolding provided by chatbot tutors based on CLT (Sweller, 1994) and SDT (Ryan & Deci, 2000).	Quasi-experiment; Pre-/post-test (Academic achievement)	RQ1: Significant improvement (Cohen's d = 0.734)
Compare chatbot-based vs. LMS-based learning	A lack of adaptive learning process in traditional video lectures (Marchand & Gutierrez, 2012) and personalized scaffolding and autonomy provided by chatbot tutors based on CLT (Sweller, 1994) and SDT (Ryan & Deci, 2000).	Paired t-test; ANCOVA (Achievement)	RQ1: Chatbot group had higher gains (F=4.838, p<.05)
Assess impact on self-directed learning readiness	Chatbots can have a positive effect on SDLRS(Alokyan et al., 2024 & Guan, R. et al., 2025) and chatbot tutor can provide social presence from the conversational interface in the chatbot tutor (Short et al., 1976)	SDLRS questionnaire	RQ2: Significant improvement in chatbot group (d = 0.809)
Examine learning experience including learner's satisfaction with chatbot	Chatbot tutors improved learning motivation with personalization (Sweller, 1994), conversational interface (Ryan & Deci, 2000), autonomy and intrinsic motivation (Ryan & Deci, 2000), and; Yin et al., 2020), and learning participation rate (Nghi, Phuc, & Thang, 2019).	Descriptive survey	RQ3: High satisfaction; Concerns about chatbot logic

These findings contribute to ongoing discussions about how to effectively integrate AI chatbot tutors in diverse educational courses. By focusing on students in liberal art courses, the study expands current understanding of inclusive AI education and highlights the potential of chatbot tutors as a scalable tool for addressing diverse learner needs, particularly in self-paced and self-directed learning contexts. For instance, the results presented in this study demonstrate that chatbots can serve as cost-effective one-on-one tutors in large-scale liberal arts courses with hundreds of students or AI literacy courses with diverse student populations. In university liberal arts education environments where physical and financial constraints preclude assigning human tutors, chatbots can serve as an institutional alternative that guarantees at least a minimal level of personalized feedback to all students.

Limitation and futher studies

This study has a limitation in that the chatbot did not provide in-depth intelligent services based on AI algorithms. From the satisfaction questionnaire, students answered that it would be more effective if the chatbot was developed to be more intelligent. Therefore, AI-based chatbot tutors might be developed to provide customized learning based on their knowledge levels, preferences, and interests, and then empirically assess the academic achievement, SDLRS, and satisfactions. Future research needs to be expanded to research on chatbot tutor that enable more diverse conversations and can provide accurate learning by clearly identifying students' cognitive levels.

In addition, these findings should be interpreted in light of the cultural and regional context of South Korea, where students generally have high digital literacy and are familiar with mobile-based learning tools (OECDa, 2023). Additionally, the widespread availability of internet infrastructure and the prominence of self-paced e-learning models in Korean universities (Lee & Lee, 2024) may have positively influenced the effectiveness of the chatbot tutor. However, these conditions may not be applicable in regions with lower technological access or in cultures where student autonomy in learning is less emphasized. Therefore, furthers studies should explore cross-cultural comparisons to validate the broader applicability of chatbot tutors in AI education.

In particular, in terms of sampling, while demographic and academic background variables such as major and gender were not included as covariates due to data constraints, these factors should be considered in future studies. Segmental analysis was not conducted in this study due to limited sample size but is recommended for further exploration. Furthermore, Study 2 of this study suffers from the limitations of a quasi-experimental design that did not allow random assignment of students. Although the homogeneity of the two groups was statistically confirmed in a pre-test and adjusted for post-test using ANCOVA, the possibility that differences in unmeasured potential variables (e.g., learning motivation and academic ability) may have influenced the results cannot be completely ruled out. This limits the internal validity of the study results.

Although this study utilized a single-factor structure of the Self-Directed Learning Readiness (SDLR) scale based on the exploratory factor analysis, this approach entails certain limitations. The first factor accounted for 28.884% of the total variance, which falls below the commonly suggested 40% threshold typically considered sufficient to justify a unidimensional factor structure. This suggests that interpreting SDLR strictly as a single construct should be approached with caution. Nevertheless, SDLR is inherently a multidimensional construct, and prior studies have also reported relatively low variance explained by the first factor—often around 28–30%—when measuring SDLR, indicating that such results are not uncommon. In this regard, the findings of the present study may still reflect the possibility that SDLR operates as a more integrated construct from the learners' perspective (Guglielmino, 1977; Hendry & Ginns, 2009; Cheng et al., 2020). Future studies are encouraged to employ confirmatory factor analysis (CFA) or structural equation modeling (SEM) to revalidate the latent structure of SDLR and to compare the fit of uni- and multi-factor models.

Finally, given that the duration of this study was relatively short, so it will be necessary to study in depth the impact of chatbot tutors through more diverse tutoring methods and over longer learning periods. In addition, in terms of SDLRS, behavioral log data further showed that the students' interaction styles might be a minimal or efficiency-driven way (e.g., skipping optional reinforcement steps when quiz answers were correct). It means that students may have limited deeper metacognitive reflection. Therefore, future research could incorporate motivational scaffolds or reflective prompts within the chatbot dialogue to support SDLR development more explicitly. It might influence the differences between two groups.

Therefore, more studies on the influence of chatbot tutors, in order to draw more generalized conclusions in the future, are suggested, since this study was conducted with a small sample size in a specific region.

7. Declarations

Availability of data and materials

The datasets utilized and/or examined in the present investigation can be obtained from the corresponding author upon a reasonable request.

Competing interests

The authors of this manuscript affirm that they have no conflicts of interest.

Acknowledgements

In this paper, some of the comments provided by reviewers during the final revision process were revised in collaboration with AI (Gemini and Chat-GPT).

Funding

This work was supported by the Soonchunhyang University Research Fund.

References

Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study, *International Review of Research in Open and Distance Learning, 19*(1), 1-5. https://doi.org/10.19173/irrodl.v19i1.3256.

Alokyan, S., Götz, F. M., & Jucks, R. (2024). How educational chatbots support self-regulated learning? A meta-analysis. *Education and Information Technologies.* https://doi.org/10.1007/s10639-024-12881-y

Burgsteiner, H., Kandlhofer, M., & Steinbauer, G. (2016). iRobot: Teaching the basics of artificial intelligence in high schools. *In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence* (pp. 4126–4127). AAAI Press. https://doi.org/10.1609/aaai.v30i1.9864

Chau, K. Y., Law, K. M. Y., & Tang, Y. M. (2021). Impact of Self-Directed Learning and Educational Technology Readiness on Synchronous E-Learning, *Journal of Organizational and End User Computing*. *33*(6), 1-22. https://doi.org/10.4018/JOEUC.20211101.oa26.

Chen, H.-L., Widarso, G. V., & Sutrisno, H. (2020). A ChatBot for Learning Chinese: Learning Achievement and Technology Acceptance. *Journal of Educational Computing Research, 58*(6), 1161–1189. https://doi.org/10.1177/0735633120929622

Cheng, S.-C., Kuo, C.-L., & Lee, H.-Y. (2020). The development and validation of a self-directed learning instrument for online learners. Journal of Educational Technology & Society, 23(2), 1–17. https://10.1016/j.ijnurstu.2010.02.002

Chang, C. Y., Kuo, S. Y., & Hwang, G. H., (2022). Chatbot-facilitated Nursing Education: Incorporating a Knowledge-Based Chatbot System into a Nursing Training Program, *Educational Technology & Society, 25*(1), 15-27. https://doi.org/10.1111/bjet.13158

Chung, C. -J., & Shamir, L. (2021). Introducing Machine Learning with Scratch and Robots as a Pilot Program for K-12 Computer Science Education. *International Journal of Learning and Teaching*, *7*(3), 181–186. https://doi.org/10.18178/ijlt.7.3.181-186

Clarizia, F., Colace, F., Lombardi, M., Pascale, F., & Santaniello, D. (2018, October). Chatbot: An education support system for students. *International Symposium on Cyberspace Safety and Security* (pp. 291–302). Springer.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers. https://doi.org/10.4324/9780203771587

Crown, S., Fuentes, A., Jones, R., Nambiar, R., & Crown, D. (2010). Ann G. Neering: Interactive chatbot to motivate and engage engineering students. In *2010 Annual Conference & Exposition Proceedings.* https://doi.org/10.18260/1-2—16687

De Bruin, K., Jacobs, G. J., Schoeman, W. J., & De Bruin, G. P. (2001). The factor structure of the Self-directed Learning Readiness Scale. *South African Journal of Higher Education*, *15*(3), 119-130. https://doi.org/10.4314/sajhe.v15i3.25333

Dogham, R. S., Elcokany, N. M., Ghaly, A. S., Daweed, T. M. A. D., Aldakheel, F. M., Llaguno, M. B. B., & Mohsen, D. M. (2022). Self-directed learning readiness and online learning self-efficacy among undergraduate nursing students, International Journal of Africa Nusing Sciences, 17, 1-5. https://doi.org/10.1016/j.ijans.2022.100490

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education*, *19*(1), 1-19. https://doi.org/10.1186/s41239-022-00362-6

Evans, H. K. (2014). An experimental investigation of videotaped lectures in online courses. *TechTrends, 58*(3), 63–70.

Fryer, L., & Carpenter, R. (2006). Bots as language learning tools. Language learning and technology. *Language Learning & Technology*, *10*(3), 8-14.

Geng, S., Law, K. M. Y. & Niu, B. (2019). Investigating self-directed learning and technology readiness in blending learning environment. *International Journal of Educational Technology in Higher Education*, *16*(17), https://doi.org/10.1186/s41239-019-0147-0

Guglielmino, L. M. (1978). *Development of the Self-Directed Learning Readiness Scale.* Dissertation, University of Georgia. Dissertation Abstracts International, 38, 6467.

Guglielmino, L. M. (1977). *Development of the self-directed learning readiness scale*. University of Georgia.

Hamzah, F., Phong, S.Y., Sharifudin, M. A. S., Zain, Z. M., & Rahim, M. (2020). Exploring Students' Readiness on English Language Blended Learning, *Asian Journal of University Education, 16*(4), https://doi.org/10.24191/ajue.v16i4.11948.

Hamzah, A. F. W. M., Ismail, I., Yusof, M. K., Saany, S. I. M., & Yacob, A. (2021). Using Learning Analytics to Explore Responses from Student Conversations with Chatbot for Education. *International Journal of Engineering Pedagogy*, *11*(6). 70-84. https://doi.org/10.3991/ijep.v11i6.23475

Hendry, G. D., & Ginns, P. (2009). Readiness for self-directed learning: Validation of a new scale with medical students. *Medical Teacher, 31*(10), 918–920. https://10.3109/01421590802520899

Holmes, W., Bialik, M., & Fadel, C. (2019**)**. *Artificial intelligence in education: Promises and implications for teaching & learning. Boston*: Center for Curriculum Redesign.

House, W. (2018). Summary of the 2018 White House summit on artificial intelligence for American Industry. In *United States. Office of Science and Technology Policy*. United States. Office of Science and Technology Policy.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist, 38*(1), 23-31. https://doi.org/10.1207/S15326985EP38014

Khodaei, S., Hasanvand, S., Gholami, M., Mokhayeri, Y., & Amini, M. (2022). The effect of the online flipped classroom on self-directed learning readiness and metacognitive awareness in nursing students during the COVID-19 pandemic, *BMC Nursing, 21(*22), https://doi.org/10.1186/s12912-022-00804-6

Kim, M., & Lee, J. (2019). Analysis of Interaction in Cooperative Learning by Academic Achievement in a Middle School English Class. *Journal of Educational Technology, 35*(1), 1–35. https://doi.org/10.17232/kset.35.1.001

Knowles, M. S. (1975). *Self-directed learning: A guide for learners and teachers.* Chicago: FolletPublishing Company. https://doi.org/10.1177/105960117700200220

Kumar, J. A. (2021). Educational chatbots for project-based learning: investigating learning outcomes for a team-based design course, *International Journal of Educational Technology in Higher Education*, *18*(65), https://doi.org/10.1186/s41239-021-00302-w.

Lee, D. (2019). A developmental plan for a conversational English learning chatbot through scenario flow. S*econdary English Education, 12*(4), 99–124. https://doi.org/10.20487/kasee.12.4.201911.99

Lee, J., So, HJ., & Ha, S. (2021) Unpacking Academic Emotions in Asynchronous Video-based Learning: Focusing on Korean Learners' Affective Experiences. *Asia-Pacific Education Researcher*, *30,* 247–261. https://doi.org/10.1007/s40299-021-00565-x.

Lee, H., & Lee, R. (2024). Transformation of Korean higher education in the digital era: Achievements and challenges. *Journal of Comparative & International Higher Education, 16*(2), 47–55. https://doi.org/10.32674/jcihe.v16i2.5847

Lin, M. P. -C., & Chang, D. (2020). Enhancing Post-secondary Writers' Writing Skills with a Chatbot: A Mixed-Method Classroom Study. *Journal of Educational Technology & Society, 23*(1), 78–92.

Marchand, G. C., & Gutierrez, A. P. (2012). The role of emotion in the learning process: Comparisons between online and face-to-face learning settings. *The Internet and Higher Education*, 15(3), 150–160.

McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (1955). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence. Retrieved from http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf

McCarthy, J., Minsky, M., & Shannon, C. (2006). A proposal for the Dartmouth Summer Research Project on Artificial Intelligence. *AI magazine, 27*(4), 12-14. Retrieved from file:///C:/Users/lois6/Downloads/1904-Article%20Text-1900-1-10-20080129.pdf

Nghi, T. T., Phuc, T. H., & Thang, N. T. (2019). Applying Ai Chatbot For Teaching A Foreign Language: An Empirical Research. *International Journal of Scientific & Technology Research, 8*(12), 897-902. https://doi.org/10.4018/978-1-59904-895-6.ch029

Nisar, T. M. (2002). Organizational determinants of e-Learning. *Industrial and Commercial Training. 34*(7). 256-262. https://doi.org/10.1108/00197850210447246

OECDa. (2023). PISA 2022 Results (Volume III) – Factsheets: Korea. OECD Publishing.

Retrieved from https://www.oecd.org/en/publications/pisa-results-2022-volume-iii-factsheets_041a90f1-en/korea_adb21d76-en.html

OECDb. (2023). OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem. OECD Publishing. https://doi.org/10.1787/c74f03de-en

Okonkwo, C. W., & Ade-Ibijola, A. (2020). Python - bot: A chatbot for teaching python programming. *Engineering Letters, 29*(1), 25-34.

Pérez, J. Q., Daradoumis, T., & Puig, J. M. M. (2020). Rediscovering the use of chatbots in education: A systematic literature review. *Computer Applications in Engineering Education, 28*(6), 1549-1565.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Sabuncuoglu, A. (2020). Designing One Year Curriculum to Teach Artificial Intelligence for Middle School. *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education*. 96-102. https://doi.org/10.1145/3341525.3387364

Sandu, R. (2017). *A Study to Analyse Economic Benefits of Cloud-Based Open Source Learning for Australian Higher Education Sector.* 1st International Conference on Business Research and Ethics (ICSBE), 9-12. https://doi.org/10.3991/ijim.v12i4.9200

Sandu, N., & Gide, E. (2019). Adoption of AI-Chatbots to enhance student learning experience in higher education in India. In *2019 18th International Conference on Information Technology Based Higher Education and Training (ITHET)* (pp. 1-5). IEEE. https://doi.org/10.1109/ITHET46829.2019.8937382

Schuett, J. (2019). A legal definition of AI, *SSRN Electronic Journal*, 10.2139/ssrn.3453632.

Sensetime (2018). Fundamentals of Artificial Intelligence. East China Normal University. Retrieved from https://www.sensetime.com/en/Service/ai_class.html

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Srikant, S. & Aggarwal, V. (2017). Introducing Data Science to School Kids. *In Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education* (SIGCSE '17). ACM, New York, NY, USA, 561–566. https://doi.org/10.1145/3017680.3017717

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction, 4*(4), 295–312. https://doi.org/10.1016/0959-4752(94)90003-5

Szczepański, M. (2019). *Economic impacts of artificial intelligence (AI)*, EPRS: European Parliamentary Research Service. 20.500.12592/0phht4.

Vázquez-Cano, E., Mengual-Andrés, S., & López-Meneses, E. (2021). Chatbot to improve learning punctuation in Spanish and to enhance open and flexible learning environments. *International Journal of Educational Technology in Higher Education* 18(33). https://doi.org/10.1186/s41239-021-00269-8

Verleger, M., & Pembridge, J. (2018). A Pilot Study Integrating an AI-driven Chatbot in an Introductory Programming Course, *Conference: 2018 IEEE Frontiers in Education Conference (FIE).*

Yin, J., Goh, T.-T., Yang, B., & Yu, X. (2020). Conversation Technology with Micro-Learning: The Impact of Chatbot-Based Learning on Students' Learning Motivation and Performance. *Journal of Educational Computing Research, 59*(1), 154–177. https://doi.org/10.1177/0735633120952067

Yu, Z. (2021). The effects of gender, educational level, and personality on online learning outcomes during the COVID-19 pandemic. *International Journal of Educational Technology in Higher Education*, 18(14). https://doi.org/10.1186/s41239-021-00252-3

Zeng, D. (2013). From Computational Thinking to AI Thinking [A letter from the editor]. *IEEE Intelligent Systems, 28*(6), 2–4. https://doi.org/10.1109/mis.2013.141

Zimmerman, M. (2018). *Teaching AI: exploring new frontiers for learning*. International Society for Technology in Education.