

The mediating effects of needs satisfaction on the relationships between prior knowledge and self-regulated learning through artificial intelligence chatbot

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Abstract

The anthropomorphic characteristics of artificial intelligence (AI) can provide a positive environment for self-regulated learning (SRL). The factors affecting adolescents' SRL through AI technologies remain unclear. Limited AI and disciplinary knowledge may affect the students' motivations, as explained by self-determination theory (SDT). In this study, we examine the mediating effects of needs satisfaction in SDT on the relationship between students' previous technical (AI) and disciplinary (English) knowledge and SRL, using an AI conversational chatbot. Data were collected from 323 9th Grade students through a questionnaire and a test. The students completed an AI basic unit and then learned English with a conversational chatbot for 5 days. Confidence intervals were calculated to investigate the mediating effects. We found that students' previous knowledge of English but not their AI knowledge directly affected their SRL with the chatbot, and that satisfying the need for autonomy and competence mediated the relationships between both knowledge (AI and English) and SRL, but relatedness did not. The self-directed nature of SRL requires heavy cognitive learning and satisfying the need for autonomy and competence may more effectively engage young children in this type of

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learning. The findings also revealed that current chatbot technologies may not benefit students with relatively lower levels of English proficiency. We suggest that teachers can use conversational chatbots for knowledge consolidation purposes, but not in SRL explorations.

KEYWORDS

artificial intelligence, K-12 education, prior knowledge, self-determination theory, self-regulated learning

Practitioner notes

What is already known about this topic

- Artificial intelligence (AI) technologies can potentially support students' self-regulated learning (SRL) of disciplinary knowledge through chatbots.
- Needs satisfaction in Self-determination theory (SDT) can explain the directive process required for SRL.
- Technical and disciplinary knowledge would affect SRL with technologies.

What this paper adds

- This study examines the mediating effects of needs satisfaction in SDT on the relationship between students' previous AI (technical) and English (disciplinary) knowledge and SRL, using an AI conversational chatbot.
- Students' previous knowledge of English but not their AI knowledge directly affected their SRL with the chatbot.
- Autonomy and competence were mediators, but relatedness was not.

Implications for practice and/or policy

- Teachers should use chatbots for knowledge consolidation rather than exploration.
- Teachers should support students' competence and autonomy, as these were found to be the factors that directly predicted SRL.
- School leaders and teacher educators should include the mediating effects of needs satisfaction in professional development programmes for digital education.

INTRODUCTION

Artificial intelligence (AI) technologies can potentially support students' self-learning of disciplinary knowledge through chatbots that engage in conversation, for example, by correcting pronunciation, spelling and grammatical errors. Some technologies have strong anthropomorphic characteristics and can interact with students (Blut et al., 2021; Pelau et al., 2021), thus providing interactive environments for self-learning. Students must take the initiative and develop strategies to learn through these technologies and engage in a proactive learning process, referred to as self-regulated learning (SRL). SRL is 'not a mental ability or an academic performance skill, but it is the self-directive process by which learners transform their mental abilities into academic skills' (Zimmerman, 2002). This directive process

is strongly associated with students' motivations to learn through digital technologies. Self-determination theory (SDT) suggests that motivation stems from three universal and psychological needs that all individuals are driven by: autonomy, competence and relatedness (Ryan & Deci, 2000). If these needs are satisfied, they can motivate self-initiated behaviour and provide energy for personal growth, joyful effort and the acceptance of challenges. This energy can foster the directive process. The satisfaction of these three needs can explain how students regulate learning through AI technologies.

Digital competence and prior disciplinary knowledge are associated with students' SRL capacity and performance in digital environments (Cleary & Kitsantas, 2017; Dong et al., 2020; Greene et al., 2010; Hirt et al., 2021; Sun et al., 2018; Taub et al., 2014; Taub & Azevedo, 2019). This implies that prior digital knowledge can affect their capacity to learn through AI technologies; this is supported by modelling studies that have examined learner technology acceptance, including the technology acceptance model (TAM) (Chiu, 2017; Davis, 1989) and the knowledge, attitudes and practice model (KAP) (Kaliyaperumal, 2004). These models suggest that computer self-efficacy is associated with attitudes towards learning and the behavioural intention to learn with technology. Thus, student AI knowledge can be viewed as a type of computer self-efficacy that affects their attitudes and behavioural intentions. Students with a good understanding of AI will understand the affordances and limitations of an AI educational application. Thus, they will feel more capable of using the application (competence), have more options to interact with it (autonomy) and be less disappointed when they fail to get satisfactory responses (relatedness) from the application.

However, AI in education is generally domain-specific (eg, pronunciation error correction or chatbots for English learning). Student prior disciplinary knowledge can predict their SRL (Taub et al., 2014) that is supported and explained by four phases in Winne and Hadwin (2008)'s Model of SRL. Students with different levels of prior knowledge process information in each of the phases differently. Students with strong prior knowledge are more likely to use more effective approach to complete their tasks for SRL. Moreover, students with good disciplinary knowledge may better comprehend the less specific or agreeable feedback given from an AI education application (competence) and thus feel less frustrated by the feedback (relatedness). They may also have more disciplinary ideas/knowledge to communicate with the application (autonomy). In summary, AI and disciplinary knowledge are likely to be related to the satisfaction of perceived needs, which would promote SRL through AI conversational chatbots.

Most education studies of AI have focused on system or application development (Song & Wang, 2020; Zawacki-Richter et al., 2019). SDT is also used as the basis for development, for example of AI-assisted decision-making design (De Vreede et al., 2021), conversational agent design (Yang & Aurisicchio, 2021) and AI algorithm development (Ferreira Chame et al., 2019). Most studies of learner technology acceptance have focused on technical knowledge (ie, computer self-efficacy or digital literacy; see Alfadda & Mahdi, 2021; Cheng, 2019; Chow et al., 2022; Dorfsman & Horenczyk, 2022; Khlaisang et al., 2021), rather than subject domain knowledge. To our knowledge, no SDT-based study has investigated how students' prior knowledge affects SRL with AI applications. This study fills this research gap from the two perspectives of needs satisfaction and disciplinary knowledge. We investigate the mediating effects of needs satisfaction in SDT on the relationships between student prior knowledge—technical and disciplinary—and SRL using a conversational chatbot. Conversational chatbots have the ability to converse with learners in natural language, process and comprehend their language, and respond based on the rules and data. They are often developed using machine learning, and Natural Language Processing technologies.

LITERATURE REVIEW

In this section, we propose using SDT as the theoretical framework to explain how the satisfaction of the three needs can mediate the relationships between SRL with AI applications. We present our hypotheses and research model.

SDT and SRL

SDT is a motivation theory that aims to explain how basic needs satisfaction affects human motivation and well-being within a social context (Ryan & Deci, 2017, 2020). It suggests that everyone has the three fundamental psychological needs of autonomy, competence and relatedness. These needs satisfaction will determine an individual's motivation to act. Autonomy refers to individuals' abilities to control their own choices and strive to progress in whatever direction they find most fulfilling; competence refers to the belief that one knows what one is doing, can complete a task and possesses the necessary knowledge and skills to succeed; and relatedness refers to the sense of belonging or connectedness to significant others, groups, or objects. The more the needs are satisfied, the greater the self-determined autonomous motivation (Chiu, 2021, 2022). SDT can therefore provide a theoretical framework for examining students' SRL abilities (León et al., 2015; Luo et al., 2021; Mouratidis et al., 2013).

This theory connects these needs to the motivational processes that encourage and foster student SRL (Grolnick & Raftery-Helmer, 2015). When students' needs are satisfied, they become highly autonomously motivated and thus effectively self-regulate their learning (Liu et al., 2014; Sierens et al., 2009). Students who feel they are autonomous demonstrate more enthusiastic, focused and purposeful learning, and exemplify self-regulation (Deci & Ryan, 2004). The satisfaction of the need for autonomy has positive consequences for students' abilities to regulate independent learning (Holzer, Lüftenegger, et al., 2021; León et al., 2015; Ng et al., 2012; Radel et al., 2014). Studies of English language learning in various digital environments have demonstrated that supporting student autonomy can encourage SRL, for example, through reading-annotation systems (Chen et al., 2020; Chen & Chen, 2014; Chen & Huang, 2014), vocabulary learning apps (Chen et al., 2019), mobile-assisted grammar learning systems (Wang et al., 2021) and online collaborative learning (Lin et al., 2017). Thus, we propose that the satisfaction of the need for autonomy can determine SRL.

Perceived competence can be regarded as a motivational belief in terms of SRL (Grolnick & Raftery-Helmer, 2015). Competence can predict students' motivations to engage in SRL (Holzer, Lüftenegger, et al., 2021; Mouratidis et al., 2013; Ryan & Deci, 2000), and they are more likely to learn independently in an environment that supports their need for competence (Grolnick & Raftery-Helmer, 2015). For example, Pelikan et al. (2021) found that students who perceived themselves as highly competent used SRL strategies more frequently in distance learning than those who felt they were less competent, due to the significant differences in their intrinsic motivation. Luo et al. (2021) found that perceived competence was positively related to perceived usefulness and enjoyment of online SRL. Wan et al. (2012) found that learners with higher levels of digital competence were able to leverage a virtual learning environment and used SRL strategies to facilitate their online learning. We therefore propose that satisfying the need for competence is related to SRL.

Students must internalise the regulation of learning in SRL. Relatedness, together with autonomy and competence, is an important part of this process (Deci & Ryan, 2004). Students who feel that they have a positive connection with their teachers are more likely to

develop identifiable and integrated regulations for learning tasks than those who feel disconnected from their teachers (Niemiec & Ryan, 2009). Those with a greater sense of relatedness and who feel more confident have been found to demonstrate more positive affect and to perform better in schools than others (Furrer & Skinner, 2003; Holzer, Lüftenegger, et al., 2021). By internalising extrinsic motivation, they can reorientate their own motivation and become more autonomous. For example, studies have shown that in a 3D virtual learning environment, students' perceptions of relatedness are associated with their intrinsic motivation (Huang et al., 2013; Ryan et al., 2006). Games can engage students in learning by satisfying their need for relatedness (Deniz et al., 2014). Student engagement in SRL is therefore likely in a learning environment that supports relatedness (Furrer & Skinner, 2003; Grolnick & Raftery-Helmer, 2015). We propose that the satisfaction of the need for relatedness is associated with SRL.

How AI and disciplinary knowledge affect needs satisfaction and SRL

AI knowledge is typically technical, and as the TAM (Davis, 1989) and the KAP model (Kaliyaperumal, 2004) suggest, can be associated with perceived competence and relatedness. In the TAM, perceived computer efficacy is strongly associated with perceived ease of use and attitudes towards using technology. Hong (2022) found that individuals with stronger AI self-efficacy were more likely to adopt AI technologies as they found them useful and easy to use. Al Shamsi et al. (2022) found that perceived usefulness was strongly positively correlated with the behavioural intention to use AI voice assistants. Malik et al. (2021) found student perceptions of chatbots (eg, perceived convenience, ease of use) positively affected their intentions to use the technology in their learning. Gado et al. (2021) focused on the KAP model and suggested that students were able to learn about AI when they felt in control (autonomy) and capable of using AI (competence). Those with knowledge of how AI works are more likely to understand the affordances and limitations of technology in supporting their learning. Thus, they will feel confident to effectively interact with AI in their learning. They may also be tolerant of receiving negative feedback and responses through AI. Moreover, AI applications that analyse students' activities in real time give students feedback and hints that benefit their SRL (van der Graaf et al., 2022). Students need to receive personalised feedback on whether they used effective learning practices, which benefit the SRL (Markauskaite et al., 2022). AI knowledge is seen as a computer efficacy that affects student motivation and intention to use AI for SRL. Accordingly, AI knowledge can therefore be associated with needs satisfaction and SRL.

AI technologies are typically applied to specific learning domains. For example, an adaptive learning system for mathematics requires a knowledge structure for generating recommendations and chatbots for English learning require data about language conversations (Adamopoulou & Moussiades, 2020). Therefore, disciplinary knowledge can influence SRL that involves AI and also the satisfaction of needs. Prior knowledge of a discipline can contribute to student motivation and their approaches to learning (Winters et al., 2008). The extensive knowledge of a subject can improve self-reflection and monitoring (Greene et al., 2008, 2010). The extent of students' prior knowledge can determine the SRL strategies they use in digital learning environments (Yang et al., 2018). This is supported by explained by Winne and Hadwin's Model of SRL (2008). The model acknowledges that SRL occurs across 4 phases—(i) definition of task, (ii) goals & plans, (iii) studying tactics and (iv) adaptations. It differs from other SRL models (eg, Pintrich, 2004; Zimmerman, 2002) by examining how information processes occur within each phase. It is expected that students with stronger prior disciplinary (English in this study) knowledge will progress through each stage differently from those with weaker prior knowledge. In the first phase, there is no difference between

students with strong and weak prior knowledge in defining what the task they were asked to do (Taub et al., 2014). However, students with strong prior knowledge who is more likely to recall how they approached a similar problem in the past will be more aware of the environmental factors such as available resources. For Phase 2, students with weak prior knowledge who are not familiar with the discipline are more likely to have difficulties to plan their learning by setting sub-goals for the tasks while those with stronger prior knowledge have no issues (Greene et al., 2008, 2010). In Phase 3, all students could deploy the planned strategies; however strong prior knowledge students could choose more effective approaches (eg, use more sophisticated and concise words) to deliver the strategies than weaker one (eg, use more simple and redundant words) (Greene et al., 2010; Taub et al., 2014). In the final phase, students with strong prior knowledge are more likely to reflect on their learning and consolidate what they have learnt, whereas students with weak prior knowledge may fail to make a meaningful reflection.

In the context of this study, a strong knowledge of English will lead to a better understanding of the responses of a language learning chatbot. The more language proficiency of these students will also lead to a better communication with the chatbot. However, students with lower levels of English language proficiency may find it difficult to approach a chatbot. A chatbot may also fail to respond appropriately to students (Adamopoulou & Moussiades, 2020). More proficient students may attempt to communicate with the chatbot in another way (Jeon, 2022) while less proficient students may give up. Students with good English proficiency will thus be more likely to feel satisfied with their levels of autonomy, competence and relatedness when learning with conversational chatbots. We therefore propose that disciplinary knowledge is associated with need satisfaction and SRL.

THIS STUDY

The aim of this study was to investigate the mediating role of students' needs satisfaction on the relationships between their English (disciplinary) and AI (technical) knowledge and self-regulated learning through AI. Our proposed research model is given in Figure 1, and we offer the following hypotheses.

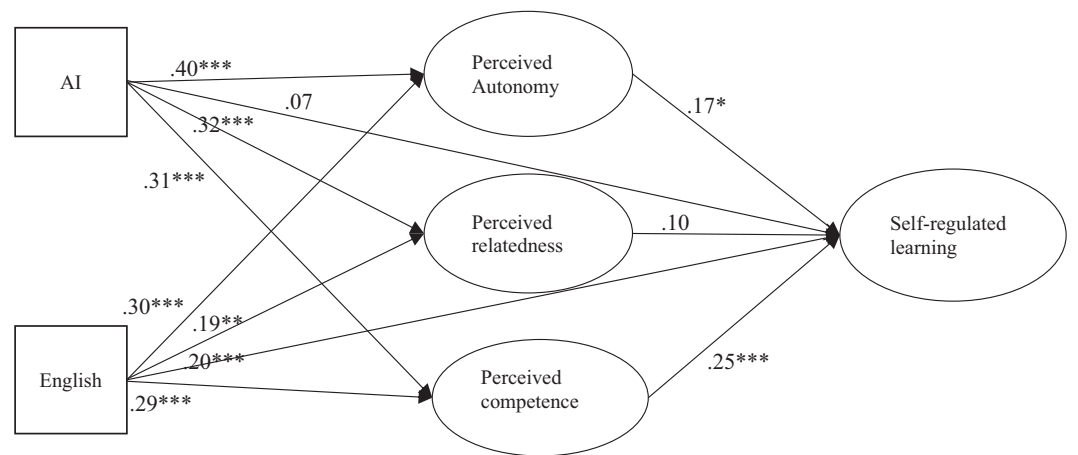


FIGURE 1 Research model. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

- H1** *English (disciplinary) knowledge will contribute positively to the satisfaction of each of the three needs.*
- H2** *AI (technical) knowledge will contribute positively to the satisfaction of each of the three needs.*
- H3** *The satisfaction of each of the three needs will contribute positively to self-regulated learning through AI.*
- H4** *Needs satisfaction will mediate the relationship between the two types of knowledge and self-regulated learning with AI.*

METHOD

Participants and research procedure

The participants were 323 9th Grade students from three middle schools in Hong Kong SAR. They were 12–14 years old (51% male, 49% female) with average academic performance standards and socio-economic status. The number of students came from each of the schools ranged from 105 to 110. They were all learning English as a second language. They had completed an AI basic unit before this study. The unit covered the six subtopics: (i) What is AI?, (ii) Does AI always work as expected?, (iii) Input-Process-Output framework and AI systems, (iv) Big data, (v) Basic learning models in AI, and (vi) model training and testing. According to the apriori sample size calculator for structural equation models, the recommended minimum sample size is 256 when the power level equals 0.8 and the numbers of latent and observed variables are 6 and 16 respectively (Soper, 2020). The sample size in this study was therefore appropriate for testing the proposed model.

We first obtained ethical approval from the corresponding author's institution and received consent from all of the participants. The students completed a 20-minute test consisting of two parts, English language and AI knowledge, before engaging in learning with a conversational chatbot in their schools. Over 5 days, they learned English with the chatbot, and then completed a 20-minute questionnaire.

To choose the chatbot for this study, three English teachers from the schools explored and picked their own preferred commercial chatbot mobile Apps to support their student learning. The corresponding author compiled their preference into a list of five Apps. The teachers tried and rated the five Apps. The highest rated chatbot App was used in this study. The App include a chatbot with different sub-themes—hello, restaurant, hotel, tickets, conversations, shopping, meeting and rental cars—that were used for student learning in study. To make conversations with the chatbot, the students could choose the suggested responses, text (typing, spelling) or voice (speaking) input their own ideas to answer the questions promoted by the chatbot. The chatbot provide the students with different options to set how they learn—listen to the audio of the questions and suggested responses, and read Chinese translation of the questions and responses. The students can set the learning environments they want. To begin the chatbot, the mother language was set to Chinese, and the learning language is English as all the student participants were Chinese. The students had choices to learn with the chatbot in any ways such as typing any input, learn more than one time. They did not have to finish all the subthemes. Figure 2 shows the screenshots of the chatbot. The AI conversational chatbot decides if student responses are appropriate for the promoted questions. It guides the students to answer by giving a gentle question and more suggested answers. The chatbot uses

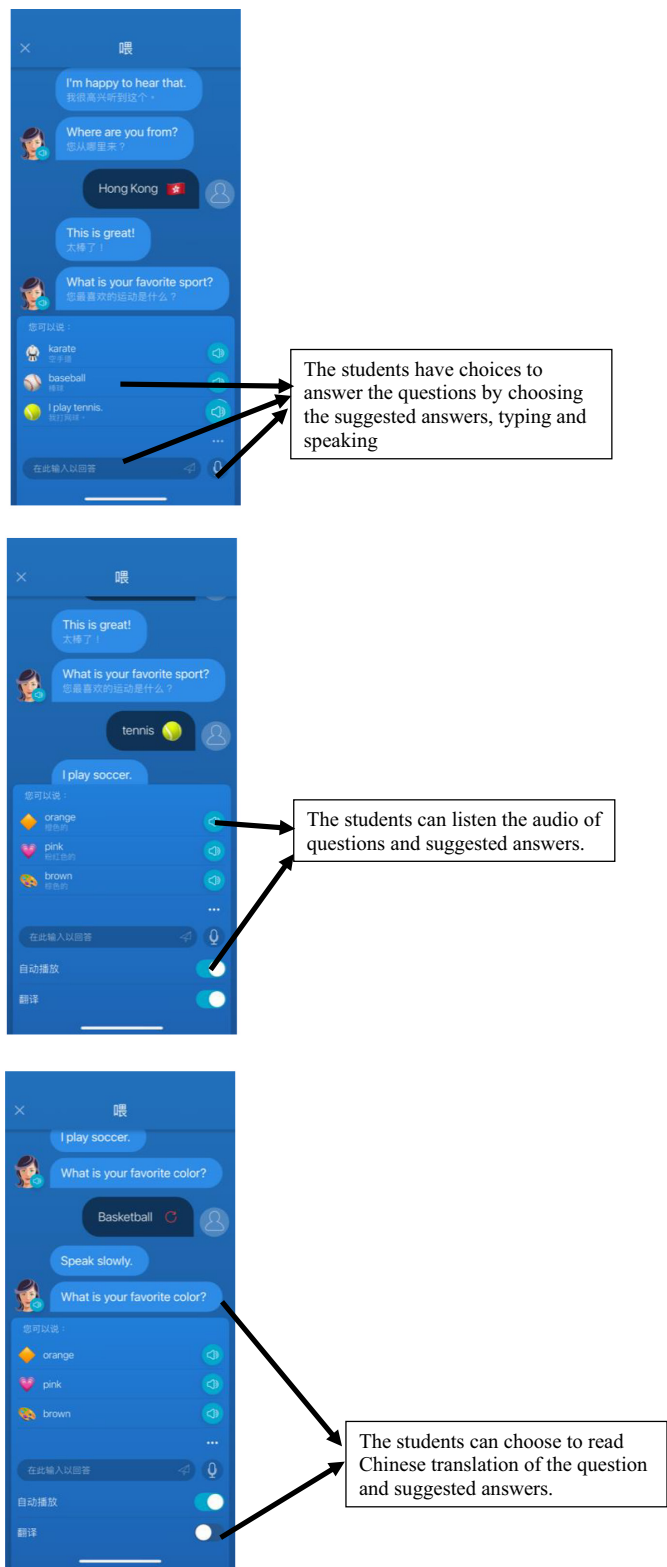


FIGURE 2 Screenshots of the chatbot.

AI speech to offer students with learning opportunities for speaking and listening, and AI read to offer students with Chinese translations for more understanding.

Questionnaire and test

In addition to demographic data, the questionnaire assessed four measures: the satisfaction of each of the three perceived needs and SRL with the chatbot. Each measure consisted of four 5-point Likert-scale items. The test consisted of an English language part and an AI knowledge part.

To assess the satisfaction of students' needs for autonomy and competence, as facilitated by the chatbot, we adapted items from Hew and Kadir (2016), which were validated by Chiu (2021, 2022) in studies that had similar demographic samples as this study. The four items for perceived autonomy satisfaction, with an original reliability of $\alpha = 0.82$, were 'I feel like I can make a lot of input in deciding how I use the chatbot in learning'; 'I feel a sense of freedom when using the chatbot'; 'I have many opportunities with the chatbot to decide for myself how to learn'; and 'I have a say regarding what input I want to learn with chatbot'. The items for perceived competence, with $\alpha = 0.71$, were 'I think I am pretty good at learning with the chatbot'; 'I have been able to learn interesting new knowledge with the chatbot'; 'I feel a sense of accomplishment from learning with the chatbot'; and 'I am pretty skilful at learning with the chatbot'. To measure the satisfaction of students' need for perceived relatedness, we adapted four items from Furrer and Skinner (2003), with $\alpha = 0.86$. The items were 'When I learn with the chatbot, I feel supported (changed to comfortable/important/valued)'.

The items measuring self-regulated learning were adapted from Sha and colleagues (2012), with $\alpha > 0.70$. The items were 'When learning English with the chatbot, I will normally set learning goals for myself so that I can decide how and what I want to learn'; 'When learning English with the chatbot, I will normally try to identify the knowledge that I do not understand well'; 'When learning English with the chatbot, I will normally ask myself questions to help me focus on what to study'; and 'When I am not sure about any English language, I will go back and try to figure it out on my own using the chatbot.'

The two parts of the test had ten questions each. The first part tested students' English language proficiency, such as 'Please write down a question for the following scenario: saying hello to a waiter, booking a table in a restaurant, buying a ticket in a cinema, asking ways to go to a museum, and looking for a bag of candy in a supermarket'. The second part tested students' basic AI knowledge, for example, 'Artificial Intelligence is about', 'Which one is an AI application?', 'Which of the following applications misuses AI technologies?', 'Bias in AI can be caused by', 'Which of the following is an example of "Data Bias" in collecting assessment scores in a class?', 'Which of the following is the correct description of "data authenticity"?', 'Which of the following will enhance model performance?', 'Which of the followings will improve AI model?' The three schools were participating schools of the corresponding authors' projects on two AI education projects—AI curriculum planning for schools (Chiu & Chai, 2020), and the development of AI and education in schools. The tests of basic AI knowledge were adopted and modified from an AI curriculum development project that involved 63 the middle schools and developed a local curriculum content and assessment (Chiu et al., 2022). Moreover, these questions were validated by three content experts in AI (two engineering chair professors and one post-doctoral fellow) and two education professors, two English teachers and two technology teachers. All the tests are marked by the teachers, and their maximum scores was 10. Accordingly, they are appropriate for this modelling study.

Data analysis

Mplus 8.3 and SPSS 26.0 were used to analyse the data. First, Cronbach's alpha (α) was calculated for every subscale in the instrument to determine its internal consistency. Second, the construct validity was examined by a confirmatory factor analysis. Last, path models were constructed and tested to examine the relationship between the variables. The effect of mediating was tested using a bootstrapping approach.

RESULTS

Descriptive statistics and reliabilities

Table 1 gives the descriptive statistics and reliabilities for each factor. The skewness ranged from -0.21 to 0.17 and the kurtosis from -0.21 to -0.08 , indicating that the data were reasonably normally distributed and could be used in the analyses. The Cronbach's α coefficients of SRL, autonomy, competence and relatedness ranged from 0.98 to 0.99 , indicating an acceptable level of internal consistency.

Measurement model

We conducted a confirmatory factor analysis to examine the construct validity. The research model had a hierarchical structure, and we found that the second-order model did not reach an acceptable level of data fit ($\chi^2 = 369.794$, $df = 98$, $CFI = 0.972$, $TLI = 0.966$, $RMSEA = 0.093$), so we deleted one item from SRL according to the model modifica-

TABLE 1 Descriptive statistics and reliabilities ($n = 323$).

	<i>M</i>	<i>SD</i>	Skewness	Kurtosis	α
1 SRL	3.37	0.87	-0.21	-0.17	0.99
2 Autonomy	3.48	0.92	-0.16	-0.55	0.99
3 Competence	3.50	0.87	-0.16	-0.40	0.98
4 Relatedness	3.25	0.71	-0.08	-0.38	0.98
5 English knowledge	6.95	2.04	-0.15	-0.71	–
6 AI knowledge	6.64	1.93	0.17	-0.73	–

TABLE 2 Factor loadings and correlation matrix for all variables.

Item	CR	Factor loadings	1	2	3	4	5	6
1 SRL	0.979	0.969 (0.949–0.996)	0.970					
2 Autonomy	0.985	0.970 (0.930–0.990)	0.473***	0.971				
3 Competence	0.981	0.964 (0.940–0.985)	0.494***	0.463***	0.964			
4 Relatedness	0.975	0.953 (0.928–0.971)	0.375***	0.410***	0.442***	0.953		
5 English knowledge	–	–	0.485***	0.528***	0.469***	0.359***	–	
6 AI knowledge	–	–	0.443***	0.566***	0.475***	0.419***	0.565***	–

Note: The bold values on the diagonal are the square root of AVE; * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$ (2-tailed).

tion indices. The modified model was examined and found to fit the data moderately well ($\chi^2 = 218.189$, $df = 84$, $CFI = 0.984$, $TLI = 0.981$, $RMSEA = 0.070$) (Hu & Bentler, 1999). As shown in Table 2, all of the indicators had standardised factor loadings above 0.60 and were significantly loaded ($p < 0.001$) on each latent variable. The composite reliability (CR) of the variables were all higher than 0.60, indicating that all of the subscales reached a high level of internal consistency. The average variance extracted (AVE) was .50, indicating that all of the subscales achieved a high level of convergent validity (Fornell & Larcker, 1981).

AI and disciplinary knowledge were treated as manifest variables. As depicted in Table 2, AI knowledge was positively correlated with SRL, $r(321) = 0.443$, $p < 0.001$, and the satisfaction of the needs for autonomy, $r(321) = 0.566$, $p < 0.001$, competence, $r(321) = 0.475$, $p < 0.001$, and relatedness, $r(321) = 0.419$, $p < 0.001$. English knowledge was also correlated with the satisfaction of the needs for autonomy, $r(321) = 0.528$, $p < 0.001$, competence, $r(321) = 0.469$, $p < 0.001$, and relatedness, $r(321) = 0.359$, $p < 0.001$. The three needs were positively associated with SRL.

Mediating effect analysis

To further examine the relationship between the variables, a path model was constructed and tested. We considered the nested nature of the data and used the maximum likelihood robust (MLR) estimator. The SEM suggested that the model shown in Figure 1 fitted the data well ($\chi^2 = 298.591$, $df = 109$, $CFI = 0.979$, $TLI = 0.973$, $RMSEA = 0.073$). The standardised direct, indirect and total effects among the variables are presented in Table 3.

The relationship between English knowledge and needs satisfaction (H1)

Student English knowledge positively and significantly predicted the satisfaction of each of the three needs of autonomy ($\beta = 0.30$, $p < 0.001$), competence ($\beta = 0.29$, $p < 0.001$) and relatedness ($\beta = 0.19$, $p < 0.01$).

TABLE 3 Standardised total, total, indirect and direct effects among variables.

Predictor	Mediating/criterion variable	Direct effect	Indirect effect	Total effect
AI	Perceived autonomy	0.40 ($p < 0.001$)	—	0.40
	Perceived relatedness	0.32 ($p < 0.001$)	—	0.32
	Perceived competence	0.31 ($p < 0.001$)	—	0.31
	Self-regulated learning	0.07 ($p = 0.295$)	0.18	0.25
English	Perceived autonomy	0.30 ($p < 0.001$)	—	0.30
	Perceived relatedness	0.19 ($p = 0.004$)	—	0.19
	Perceived competence	0.29 ($p < 0.001$)	—	0.29
	Self-regulated learning	0.20 ($p < 0.001$)	0.14	0.34
Perceived autonomy	Self-regulated learning	0.17 ($p = 0.015$)	—	0.17
Perceived relatedness	Self-regulated learning	0.10 ($p = 0.068$)	—	0.10
Perceived competence	Self-regulated learning	0.25 ($p < 0.001$)	—	0.25

The relationship between AI knowledge and needs satisfaction (H2)

Student AI knowledge positively and significantly predicted the satisfaction of each of the three needs of autonomy ($\beta = 0.40$, $p < 0.001$), competence ($\beta = 0.31$, $p < 0.001$) and relatedness ($\beta = 0.32$, $p < 0.001$).

The relationship between needs satisfaction and SRL (H3)

The results indicated that autonomy significantly predicted SRL ($\beta = 0.17$, $p < 0.01$), as did competence ($\beta = 0.25$, $p < 0.001$), but relatedness did not significantly predict SRL ($\beta = 0.10$, $p > 0.05$).

The mediating role of needs satisfaction (H4)

We used a bootstrapping approach to examine the mediating effect of needs satisfaction. This approach does not require distribution assumptions; thereby, it avoids the issue of coefficient product testing violating these assumptions. We calculated 95% confidence intervals (CIs) for the effects of AI and English knowledge on SRL through bootstrapping with 1000 random samples, to further examine the mediating effects of autonomy, competence and relatedness. The coefficient of the indirect effect of AI knowledge on SRL was 0.143 (95% CI = [0.097, 0.293]) and the direct effect was not significant. In this indirect mediation, the coefficient of the indirect effect of English knowledge on SRL was 0.176 (95% CI = [0.087, 0.221]), as the direct effect was significant and pointed in the same direction as the indirect effect, indicating complementary mediation. The 95% CIs did not contain 0, and thus both AI and English knowledge were significant indirect predictors of SRL through needs in SDT. The total effects of AI knowledge and English knowledge on SRL were 0.143 and 0.176 respectively. The non-significant specific indirect effects via relatedness indicated that the mediation of needs in SDT mainly resulted from autonomy and competence. Thus, our results indicated that the three forms of needs satisfaction partially mediated the relationships between AI knowledge and SRL and between English knowledge and SRL.

DISCUSSIONS AND CONCLUSIONS

This study provides a useful examination of the mediating role of the satisfaction of students' needs in the relationship between their knowledge of English (disciplinary) and AI (technical) and their SRL through AI in the K-12 context. This study makes three empirical contributions and two theoretical contributions to the literature. We also offer practical suggestions for researchers, practitioners and educational technology developers.

Empirical implications

First, we found a significant direct effect between English language skills and SRL (H1), which is aligned with the studies of Greene et al. (2008, 2010), and Taub and colleagues (2014). The students with good English profanely engaged more in a self-directive process to apply their abilities to English learning with the chatbot. Prior disciplinary knowledge could predict the SRL in digital learning environments. This is also explained by the 4 phases in Winne and

Hadwin (2008)'s model of SRL. Students with good English proficiency are more likely to use an effective approach to complete the tasks in each of the phrases.

Second, we found an insignificant direct effect between AI knowledge and SRL (H2). These findings suggest that having good AI knowledge is less likely to motivate student engagement in the self-directive process, possibly because the process requires students to use subject content knowledge to interact with the chatbot (Zimmerman, 2002). Chatbots do not understand complex expressions (Bibauw et al., 2019; Jeon, 2022; Yin & Satar, 2020), and good vocabularies are required to communicate with the chatbot. In addition good AI knowledge alone does not facilitate the self-directive process, because the use of the chatbot may change students' learning behaviour but not their learning cognition and perception (Kumar, 2021). In addition, the chatbot actively asks the students questions and responds to their questions in a learner-friendly environment. This does not require sophisticated technical knowledge, as the students encounter very few technical problems. Our results together imply that English knowledge is a prerequisite for self-regulated English learning using a chatbot. The students are required to pay attention to language conversation rather than to how the chatbot processes their input. Our findings differ from those of studies that identified a relationship between computer self-efficiency and the motivation to learn through technology (such as the original TAM; see Alfadda & Mahdi, 2021; Cheng, 2019; Chow et al., 2022; Dorfsman & Horenczyk, 2022; Khlaisang et al., 2021). Most studies have used generic technologies (eg, mobile device, LMS), and AI educational technologies are often focused on a specific discipline. Our study identifies an underexplored empirical relationship between prior knowledge and SRL through AI technology.

Third, we found that satisfaction of the needs for autonomy and competence were predictors (H3) of SRL, and mediators (H4) in the relationships between prior knowledge (AI and English) and SRL. Our findings indicate that the two types of knowledge indirectly predict SRL via the need for autonomy and competence. However, satisfaction of the need for relatedness was not a mediator in the relationships between prior knowledge (AI and English) and SRL. These findings are in line with the studies by Alrabai (2021) and Rutten et al. (2012), who suggested that satisfying the needs for autonomy and competence are important mediators of learning motivation or cognitive outcomes, but the effect of relatedness is insignificant. Thus, a chatbot that supports the needs for autonomy and competence can encourage self-direction. The theory of mind in AI (Langley et al., 2022) suggests that the process is primarily cognitive rather than emotional, as social information can be processed regardless of whether it comes from AI or another person (Lee, 2004). An appreciation of the subject (ie, English) rather than the chatbot itself can encourage students to invest cognitive effort in the process. This supports the findings of Kumar (2021), who suggests that chatbots can improve student learning performance but not affective-motivational learning outcomes such as perceptions of learning and motivation. However, whether the interaction between students and chatbots stems from an innate response to social information or from the emotional attachment as learning partners remains unclear. Further studies are required to explore how the anthropomorphic characteristics of AI affect human cognitive processes.

Finally, our results indicate that supporting the needs for autonomy and competence rather than relatedness is more important when encouraging student SRL through chatbots. Student experiences of SRL may therefore be more cognitive in nature. Their cognitive processes can thus be explained by the desire to satisfy the needs of autonomy and competence (Chiu, 2022; Sierens et al., 2009). Our findings support those of Holzer and colleagues (2021), and suggest that relatedness in general is not positively related to SRL, as the assumptions in SDT are context-dependent and student psychological needs vary between education sectors and learning environments (Ryan & Deci, 2000). In addition, SRL is a complex issue that involves cognitive, metacognitive, behavioural and motivational

aspects of learning, so additional research is needed to determine the predictors of SRL with AI applications.

Theoretical contributions

This study contributes to learner technology acceptance research by identifying the type of prior knowledge and needs satisfaction as important factors. We distinguish student knowledge into disciplinary (ie, English) and technical (ie, AI) knowledge. Most research on technology acceptance (eg, TAM; Alfadda & Mahdi, 2021; Cheng, 2019; Chow et al., 2022; Dorfsman & Horenczyk, 2022; Khlaisang et al., 2021) suggests that technical knowledge such as computer self-efficacy and digital competence influences the motivation to learn through technology. We suggest that disciplinary knowledge is more influential than technical knowledge when learning with domain-based technologies. This finding may encourage researchers to re-examine their theories and models by identifying the relationships between discipline and the type of technology (domain vs. non-domain).

Second, the research into psychological needs in AI for education remains limited (Al Shamsi et al., 2022; Gado et al., 2021; Seufert et al., 2021). This study contributes to SDT-based research by examining AI educational technology and presenting evidence of how needs satisfaction can explain the development of SRL in English. The digital learning environments investigated in most SDT research are non-disciplinary, such as LMS and games (Bedenlier et al., 2020; Chiu, 2021; Chiu et al., 2022; Xie & Ke, 2011). We take a different perspective, emphasising how needs satisfaction can inform AI disciplinary educational technology.

Practical suggestions

This study provides insights for teachers into how prior knowledge can affect student SRL using conversational chatbots for English language learning. Our findings have three practical implications for K-12 teachers and school leaders. First, teachers should be aware that current AI chatbot technology may not be sophisticated enough for SRL in school language learning, although personalised learning is a common approach in such technologies (Bibauw et al., 2019; Jeon, 2022; Vázquez-Cano et al., 2021). Not all students are capable of regulating their learning with chatbots. Current chatbot technology may be appropriate for more advanced students who have good language proficiency. We suggest that teachers can use chatbots for knowledge consolidation rather than exploration (Fryer et al., 2019; Vázquez-Cano et al., 2021), and thus in the final stages of learning. This can be more effective in increasing students' English language knowledge.

Second, teachers should support students' competence and autonomy, as these were found to be the factors that directly predicted SRL. They are essential in shaping student motivation and thus SRL in an AI-interactive environment. Teachers should support student competence by giving step-by-step guidelines or sample phrases, sentences and questions (Hartnett, 2015). This can encourage successful learning experiences with chatbots. The students can learn from example conversations and develop their own input and ideas in learning through interacting with chatbots.

Third, K-12 school leaders can offer professional development training in AI technology to teachers, as this technology is still new and challenging (Chiu et al., 2022). Our results reveal how students' prior knowledge can determine the effectiveness of SRL with conversational chatbots and also highlight their affordances and limitations. School leaders and teacher

educators should include discussion of these characteristics in professional development programmes for digital education.

Finally, we provide insights for researchers and developers of AI conversational chatbots. We reveal that current chatbot technologies are not sophisticated enough for young students with limited English language proficiency. These students often have no idea about what to ask or offer meaningless input. Thus, the developers should use more data from weaker students or identify their levels of expertise (academic skill or cognitive capacities) for further conversations (Chiu & Mok, 2017).

LIMITATIONS AND FUTURE DIRECTIONS

This study has four main limitations. First, the proposed model is examined using structural equation modelling. Studies using other research methods should be conducted to validate our findings. We suggest using intervention-based or experimental studies to test the effectiveness of chatbots in terms of language learning. Second, the participants are non-native English speakers in Hong Kong middle schools. Their native Chinese is more a graphical language (Chen & Zhou, 2010). It would be helpful for future research to use a sample of non-native English speakers familiar with a non-graphical language such as Thai. Third, our research relies on questionnaire surveys as a quantitative approach, but this does not allow in-depth analysis of the relationships between needs satisfaction and prior knowledge in terms of SRL with chatbots. Further studies should take a more qualitative approach to gain a more thorough and deeper understanding of this issue.

Our empirical implications also suggest future research directions. These include (i) establishing the empirical relationship between prior knowledge and SRL using AI technology; (ii) exploring how the anthropomorphic characteristics of AI (conversation in chatbots) affect human cognitive processes; and (iii) determining the predictors of SRL with AI applications.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interests between the author and participants.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

This study got ethical clearance from the author's university.

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