Teacher Support and Student Motivation to Learn with Artificial Intelligence (AI) based Chatbot

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Abstract

As Artificial Intelligence (AI) advances technologically, it will inevitably bring many changes to classroom practices. However, research on AI in education reflects a weak connection to pedagogical perspectives or instructional approaches, particularly in K-12 education. AI technologies may benefit motivated and advanced students. Understanding the teacher's role of student motivation in mediating and supporting learning with AI technologies in the classroom is needed. This study used self-determination theory as the undergirding framework to investigate how teacher support moderates the effects of student expertise on needs satisfactions and intrinsic motivation to learn with AI technologies. This experimental study involved 123 Grade 10 students, and used chatbots as AI-based technologies in the experiment. The analyses revealed that intrinsic motivation and competence to learn with the chatbot depended on both teacher support and student expertise (i.e., self-regulated learning and digital literacy), and the teacher support better satisfied the need for relatedness, and it less satisfied the need for autonomy. The findings refined our understanding about the application of self-determination theory and expand the pedagogical and design considerations of AI application and instructional practices.

Keywords: AI in education; motivation; self-determination theory; teacher support; student expertise; chatbots

AI in education (AIEd) refers to the application of AI technologies, such as chatbots, automatic marking systems, intelligent tutoring systems, and student performance prediction platforms that support and enhance education (Chiu, et al., 2023). Most AIEd studies have focused on the development of AI tools and systems involving the effectiveness of the learning algorithms, as well as the ethics of AI and the fundamental rights of learners using AI (Berendt et al., 2020; Chiu et al., 2022; Cope et al., 2020; McStay, 2020; Luckin & Cukurova, 2019). A systematic review on AIEd suggests that AI technologies have been integrated into four key educational domains - teaching, learning, assessment, and administration (Chiu, et al., 2023). For example, intelligent tutoring systems could recommend subject content and tasks, and teaching strategies; chatbots could offer; chatbots could give feedback to foster student self-regulated learning, and answer students' inquiry on administration; automatic marking systems could offer more effective grading. These studies have highlighted that current AIEd research reflects a weak connection to pedagogical perspectives or instructional approaches, and neglects the complex multi-faceted challenges and risks of learning and teaching with AI (Guilherme, 2019; Holmes et al., 2019, p.165; Williamson & Eynon, 2020; Zawacki-Richter et al., 2019). How students interact and use AI technologies in a pedagogically sound manner remain unclear. Hence, it is necessary to better understand the utilization of AI in today's classroom.

Research informs us that students' motivation has a direct impact on their learning approaches, their engagement level, their persistence in accomplishing goals, and influences their thinking processes and learning approaches (Chiu, 2021a, 2021b, 2022). It is likely that students' motivation to interact and learn with AI technologies will be affected by how well such technologies are applied in practices. As adolescence is a particularly precarious stage for motivation (Eccles et al., 1997), studying the student motivation in schools is crucial in both research and practice in AIEd. It is therefore crucial to explore the relationship between student motivation and AIEd. In addition, understanding the teacher's role, as a core facilitator of student motivation and academic progress, in mediating and supporting learning with AI technologies in the classroom, will provide a clear understanding of how such technologies could be used in practice.

To help conceptualise motivation, Ryan and Deci (2017; 2020) propose Self-determination Theory (SDT). SDT has been validated by numerus studies in various domains, including the learning motivation of K-12 learners. It argues that for learners to become autonomously motivated, which is the preferred motivation for learning that can lead to greater engagement and stronger persistence, learners psychological needs (autonomy, competence and relatedness) need to be satisfied. With more advanced AI-based learning tools constantly being developed, understanding their role in relation to student motivation through the use of SDT-research will continue to grow (Chiu, 2022; Peters et al., 2018). Indeed, Ryan and Deci (2020), recently called for scholars to further investigate the affordances of modern technology to motivate student learning as well as student motivation to use the technology for learning. However, to date, there has been no SDT-based research exploring AIEd in K-12 contexts.

Literature sees the potentials of using AI for learning, but still have not clearly showed its scientific impact on learning, particularly in school education (Williamson & Eynon, 2020), for example, chatbots as an AI technology was suggested to benefit motivated and/or high achieving students more (Kolchenko, 2018; Shawar & Atwell, 2007). Students with different expertise may respond differently to learning with the technology; therefore, the roles of the technology vary on those students. How teachers teach plays an important role in motivating students to learn in schools (Pitzer &

Skinner, 2017). Teacher practices in designing learning activities, providing resources and interacting with students to support student needs in AI-enhanced environments needs more attention, but it is currently understudied (Kolchenko, 2018; Pitzer & Skinner, 2017). Accordingly, this current study aims to help us better understanding this exciting but emerging and under-researched field of AIEd in K-12 education by investigating the roles of AI technology in student classroom learning. More specifically, it explored the use of chatbots (an AI-based learning tool) and the mediating role of teacher support on student motivation to learn with chatbots from the perspectives of needs satisfaction.

Literature Review

AIEd Research

AIEd research aims to support and critique the development of AI and AI-based tools and systems, and investigate how to use them to improve learning and teaching (Holmes et al., 2019; Williamson & Eynon, 2020). Much of the research to-date, has focused on inventing and developing learning algorithms or training new learning models to develop new educational tools and systems. These tools and systems are often based on learning sciences and cognitive sciences (Perrotta & Selwyn, 2020; Luckin & Cukurova, 2019). For example, using knowledge of learning process, AI tool and system developers can train a predictive machine learning model in development of adaptive learning systems (Perrotta & Selwyn, 2020). The result of which might be an AI-based tool for training specific skills in which learners engage in small units of learning with embedded formative assessment, which help the system learn the learners' needs, and recommend student learning paths (Cepeda et al., 2006). Relevant studies have revealed that well-designed AI systems such as, OLI learning course, developed by the Carnefie Mellon University (Lovett et al., 2008) and Cognitive Tutor (Pane et al.,

2014) can have positive impacts on student learning. AI systems can significantly improve the effectiveness and quality of student learning, at least in higher educational contexts (Luckin & Cukurova, 2019; Mc Arthyr et al., 1995 p. 42). These positive results have been interpreted by some as indicators of the potentially profound transformational effect of AIEd and suggest that AI technologies can help automate traditional methods of teaching and learning (Williamson & Eynon, 2020). However, doubts about the value of AI educational technologies remain due to the limited evidence of their effectiveness at scale or in other levels of education, i.e., K-12 (Bake, 2016; Kolchenko, 2018). Overall, empirical studies on AIEd in schools are scarce. How teachers use AI technologies pedagogically and their roles in learning in classrooms remain unclear.

Student Needs Satisfaction and Technology

In SDT, Ryan and Deci (2017, 2020) categorize various intrinsic and extrinsic sources of motivation, and differentiate between autonomous (high-quality) and controlled motivation (low-quality). They also propose that all individuals have three basic psychological needs –autonomy (feeling they have choices and ownership), competence (feeling capable and proficient), and relatedness (feeling connected and loved). Satisfying these basic needs can foster a high-quality form of motivation that leads to better engagement and persistence in activities. While, thwarting any of these three needs may be detrimental to engagement and performance in activities. The theory has been widely and effectively applied in in-person and online classrooms with positive outcomes (See Ryan & Deci, 2020 for various examples). Understanding needs satisfaction has the potential to transform how teachers teach and prepare lessons using technology. To support autonomy, teachers can give and endorse students' choices, offer students flexibilities to complete their assignments in various formats, and provide explanatory rationales or explain the relevance of tasks to students learning goals, when choice is forced (Chiu et al., 2022; renshaw et al., 2016). These actions will increase students' performance because they will perceive greater ownership over the learning tasks. To cultivate competence, teachers can standardize the learning materials, design cognitive-effective resources (Chiu et al., 2017, 2021), organize peer moderation to encourage students to share ideas in classes (Xie & Ke, 2011), and give feedback related to competence (Chiu, 2021a, 2022). In such social environments, students feel competent and confident to take on challenges. To encourage relatedness, teachers can develop warm, caring, and positive learning environments by providing personal praises and comments to students, eliciting and valuing their feedback, and facilitating collaborative activities (Xie & Ke, 2011) and small group discussions. In such welcoming, safe and comfortable environments, students will feel more connected to peers and teachers and, therefore, more engaged in learning. In sum, research has shown that satisfying the three psychological needs could better engage students in learning. In other words, AI-based tools such as chatbots and their use in the classroom should support the three needs for high-quality form of motivations.

Chatbots and Student Expertise

Chatbots are AI-based applications developed to mimic human interactions and engage in real-time spontaneous conversations with humans. Their role within classroom learning, particularly in language education, is tangential (Fryer et al., 2019; Shah et al., 2016; Yin et a., 2021). Previous relevant studies focus on how they comprehend human conversations and motivate students learning. Research on chatbot competency (i.e., comprehension) suggested that their ability to engage in 'authentic-like' conversation can be limited. First generation chatbots developed in the 2000s as language learning tools, could be frustrating for learners to interact with. For example, students needed to spell input correctly (Coniam, 2008). Furthermore, chatbots were not always able to respond to the student questions accurately on track the flow of a conversation (Fryer et al., 2019; Yin et a., 2021). Often their responses were vague and sometimes mislead students (Fryer et al., 2019). These early developed chatbots had very little educational values. However, over the last decade, chatbots have improved (Coniam, 2014; Fryer et al., 2019; Shah et al., 2016; Yin et a., 2021). For example, Shah and colleagues (2016) found modern chatbots have significant higher scores from users than first-generation chatbots that were built using early natural language processing. A chatbot evaluation study conducted by Coniam (2014) revealed that most modern chatbots are able to present grammatically acceptable responses. These improvements increase the potential for chatbots to be used for learning, but more evidence is needed to relate chatbots to learning success (Fryer et al., 2019). For example, Smutny and Schreiberova (2020) reported that their evaluation of 47 educational chatbots on Facebook messenger platform for higher education indicated that chatbots were in the early stage of becoming teaching assistant, and needed improvements. Notwithstanding the lack of major breakthroughs in chatbot language communication skills, students still find them comfortable, interesting and fun to play with (Fryer et al., 2019; Hill et al., 2015; Yin et a., 2021). For example, a study conducted by Hill and colleagues (2015) revealed that university students held significantly longer conversations with chatbots than with other humans, however, the users used shorter sentences with simple vocabularies for communications. Yin and colleagues (2021) found that university students who engaged with chatbot-based learning environments significantly had greater intrinsic motivation than those who did not. These findings imply that students felt at ease and had greater conversational engagement when learning with chatbots. When chatbots are seen as a playful application, that does not offer threatening conditions, they can encourage students to keep trying to express their ideas during interacting with them. Therefore, in learning and teaching, one of the potential roles for chatbots is to motivate students by inspiring their curiosities and increasing their persistence (Fryer et al., 2019).

Most of these studies were conducted in higher education. In K-12 education, students can have less sophisticated self-regulated learning skills and a wider diversity of learning needs. Therefore, chatbot competency is crucial to school-age students, particularly low achieving or proficient student (Fryer et al., 2019; Kolchenko, 2018). These students need more accurate responses from chatbots, and are more likely to give up easier when feeling confused or facing failure during learning. Past and recent research related to the effects of learning technology on student expertise indicated a trend that instructional design with technology could have differentiated benefits low or high achieving students (Kalyuga, 2007; Kalyuga, Rikers, & Paas, 2012; Chiu et al., 2020; Chiu & Mok, 2017). The main recommendation of the research is that more effort should be made to cater for learner diversity. For chatbots, it is also likely that high achieving students will benefit more from interacting with them than low achieving students. For example, if responses from chatbots are confusing or vague, high achieving students are more able to ask additional follow-up questions to clarify the responses or ask more specific questions. However, low achieving students may not know how to interpret the response or take actions to clarify understandings, while their questions may be inaccurate, increasing the likelihood of a confusing responses from the chatbot. Hence, how school students with different learner expertise interact with chatbots deserves further examination.

Chatbots and Needs Satisfaction

In line with SDT, if chatbots can be utilized as part of an inquiry instructional approach that allows students to choose their own questions and responses (Shawar & Atwell, 2007; Autonomy in SDT), receive immediate feedback (Smutny & Schreiberova, 2020; Yin et al., 2021; competency), and feel like they are talking to a human-like machine (Relatedness), they could have a positive impact on learners' autonomous motivation. SDT enables researchers to more accurately describe how needs support from chatbots might lead to autonomous motivation, which is key to learning with AI technologies. Employing SDT, and undertaking a careful and deep analysis of needs satisfaction that students with different expertise experience on interacting with chatbots, might help researchers understand the role of AI technologies in K-12 classroom settings.

The Present Study

Research Goals and Questions

SDT-based research on learning and technology has not only suggested instructional designs, but also emphasized the importance of teacher needs support (Alamri et al., 2020; Chiu, 2021a, 2021b, 2022; Trenshaw et al., 2016). Students with different levels of expertise, respond differently to instructional design (Kalyuga, 2014). Students with stronger expertise may perceive stronger needs support from chatbots than those with weaker expertise, resulting in greater intrinsic motivation to learn with chatbots alone (Shawar & Atwell, 2007). Therefore, teacher support or guidance is more important to novice when learning with chatbots. For example, a chatbot could be a main collaborator /facilitator / teacher for advanced students, but a proxy one for novice. Its roles in teaching within classrooms remain unclear.

Student self-regulated learning skills (SRL) and digital literacy (DL) are prerequisite for effective technology enhanced learning. For example, successfully discussing a topic in forums, analyzing information collected from web, and making a multimedia presentation require SRL and DL (Chen & Jang, 2010; Ng, 2012). Therefore, students with different levels of SRL or DL could have different perceptions towards chatbots despite chatbots being able to offer personalized learning experiences. The perceptions could influence the actions taken for the feedback they receive. For instance, a student who is aware that chatbot's comprehension of speech is dependent on speech quality (DL) may choose to repeat in clearer voice and slower speech; or change to text input when interacting with chatbot (SRL). The present study aims to investigate how teacher support and student expertise (either SRL or DL) affect motivations to learn with chatbots, from the perspectives of needs satisfaction. More specifically, it examines whether teacher support moderates the effects of student expertise on student needs satisfaction and motivations to learn with chatbots. Accordingly, the two research questions are

RQ1: Does teacher support moderate student expertise and needs satisfaction when learning with chatbots?

RQ2: Does teacher support moderate student expertise and intrinsic motivation to learn with chatbots?

The hypotheses for RQ1 and RQ2 are

(H1) There are significant interaction effects of teacher support and student expertise on perceived competence and intrinsic motivation to learn with chatbots.

(H2) There are no significant effects of teacher support and student expertise on perceived autonomy and relatedness to learn with chatbots.

(H3) The students with teachers support significantly perceive less relatedness and stronger autonomy than the students without.

In this experimental study, the treatment was teacher support, and the two experimental groups were: students learning with (teacher support group: TS) and without (no teacher support group: NTS). The students were randomly divided into the TS and NTS groups.

Participants

One hundred and twenty-four Grade 10 school student participants (age: 15 - 17) who learn English as second language were recruited from a funded university and school partnership project; one participant was removed from this study due to missing data. The participants have average academic performance, based on standardised local government assessments. The TS and NTS group sizes were 61 (32 girls, 29 boys) and 62 (32 girls, 30 boys), respectively.

Measures in the Questionnaires

The pre-questionnaire measured SRL and DL; the post-questionnaire measured three needs satisfactions and intrinsic motivation to learn with chatbots. All the items in the questionnaires were rated on a 5-point scale (1 = strongly disagree; 5 = strongly agree)

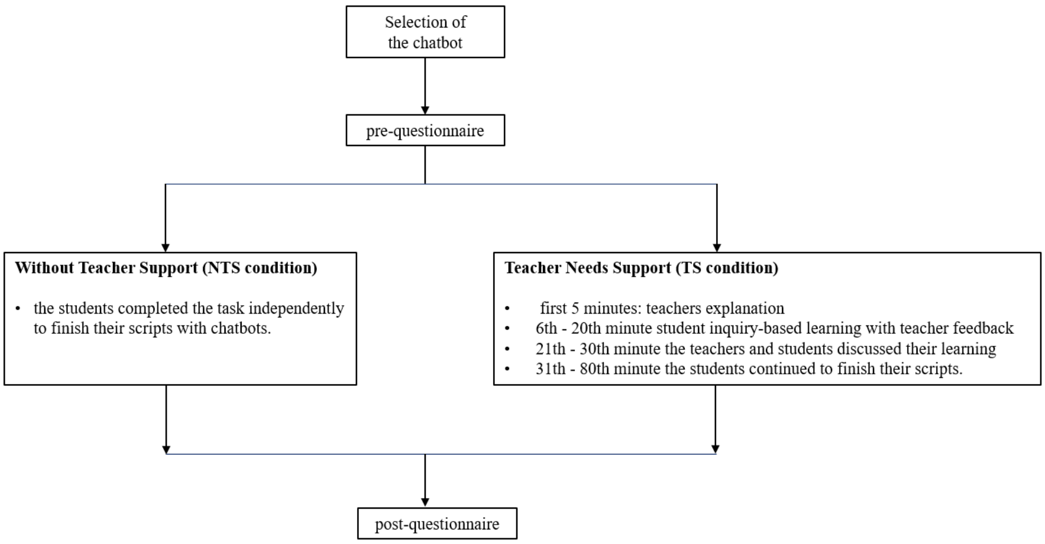
Self-regulated learning skill. Three items were adapted from Self-Regulation Learning Questionnaire (Black & Deci, 2000; α = .80). They were "*I will participate actively in learning English language bcause a solid understanding of English language is important to my intellectual growth.*", "*I am likely to follow my teacher's suggestions* *for studying English language, because he/she seems to have insight about how best to learn the language.*", and "*The reason that I will work to expand my knowledge of language is because it is a challenge to really understand how to apply English language in real life.*"

Digital Literacy. Six items related to digital literacy were adopted from the study of Ng (2012), which had an acceptable level of reliability (α = .90), which was adopted by Prior and colleagues (2016). They were "*I know how to solve my own technical problems.*" "*I can learn new technologies easily.*" and "*I know about a lot of different technologies*.", "*I am confident with my search and evaluation skills in regard to obtaining information from the web*.", "*I am familiar with issues related to web-based activities*.", and "*Technology enables me to collaborate better with my classmates on project work and other learning activities.*".

Intrinsic motivation. Three items were adapted from the interest/enjoyment scale of the Intrinsic Motivation Inventory (IMI). They were "*I enjoyed learning with the chatbot very much.*", "*Learning with the chatbot was fun.*", "*I would describe learning with the chatbot as very interesting.*" (McAuley et al., 1989; α = .89). IMI has been used in many experiments related to intrinsic motivation and self-regulation.

Needs satisfaction. Three subscales from the Basic Psychological Needs Scale–Revised (BPNS-R) were used (Chen et al. , 2015; α > .71). Items for autonomy satisfaction were "*I felt a sense of choice and freedom in the learning activity I undertake.*", "*I felt I learned activity what really interests me.*" and "*I felt that my decisions reflected what I really wanted in the learning activity.*"), competence satisfaction were "*I felt competent to achieve my learning goals.*", "*I felt confident that I learned the topic well.*" and "*I felt capable at what I did in the lesson.*", relatedness satisfaction were "*I felt that the lesson was a caring environment.*", "*I experienced a* *warm feeling in the activity that I spent time in.*" and "*I felt close and connected with the activity, which is important to me.*".

Figure 1. Research Procedure



Research Procedure

Figure 1 shows the overall research procedure. To select an AI-based chatbot for this study, four experienced teachers were invited to review and rate 10 commercial chatbots specifically designed for Hong Kong to see whether they were appropriate for use with secondary school students. Commercial chatbots were chosen as they add authenticity to the learning experience - similar to using a real storybooks instead of textbooks. The teachers were asked to explore the chatbots and rate them based on their suitability for the target learners. The highest rated chatbot was chosen for the study. The chatbot selected was designed and operationalised by the Mass Transit Railway (MTR), a local railway company in Hong Kong, see Figure 2. The chatbot was originally designed to serve as the MTR's Virtual Ambassador. It was designed to help commuters, particularly tourists, plan journeys, learn more about MTR managed shopping malls and respond to inquiries regarding the "MTR Points" reward scheme.

The chatbot is built on the following technologies: InfoTalk-Processor - A multilingual and mixed-lingual technology for natural Language processing and natural language understanding, and InfoTalk-Receptionist: A technology used within the commercial sector that has been engineered to answer common questions from consumers.

The experiment was conducted in the school where the participants studied. Three weeks before the experiment, the participants were informed of the aims and procedures of the study with informed consent collected. Two days after the consent was collected, the participants completed the pre-questionnaire.

In the experiment, the task was to create a conversational English language script for tourists. The chatbot is seen as an inquiry or quest answer provider during learning; the students used inquired-based approach to complete the task by interacting with the chatbot, clarifying and reflecting the data from the chatbot, and asking follow-up questions. The students in both experimental groups learned with individual computers in groups of 20 divided over six teaching sessions. In the NTS condition group, the students completed the task independently, i.e., they had free choice of how and when to use the chatbot. In the TS condition, the participants completed the task with teacher support. In the first 5 minutes the four teachers explained what the task and chatbot were, and endorsed the tasks the students chosen; from the 6th to 20th minute the participants used the chatbot and the teachers gave specific feedback on their usage; from 21th to 30th minute the teachers and students discussed their learning with warm, welcoming and positive atmosphere, the teachers praised students work; from 31th to 80th minute the students continued to finish their scripts. Finally, the teachers gave feedback on their learning. At the end of the experiment, the participants completed the post-questionnaire and we thanked them for their participation.

Analysis Approach

Breaking the participants into the two groups, as with a median split, results in a loss of analysis power (Chiu & Mok, 2017). Therefore, to answer the research questions, the corresponding author used moderated multiple regressions using student expertise and teacher support as predictors to analyze the data from the questionnaires. The main software used is SPSS.

Results

Moderated multiple regressions using student expertise and teacher support as predictors were used to analyze the data from the questionnaires. Descriptive statistics for all of the variables are presented in Table 1. Moderated multiple regression analyses on dependent variables - perceived autonomy, competence, relatedness and intrinsic motivation were executed. Two models for each of the dependent variables were examined. In Model 1, only the independent variable (either SRL or DL) and the moderator teacher support were entered. In Model 2, the interaction term independent variable X teacher support as predictors were added. Comparison of the two models and examination of the beta values of the predictors in Model 2 allows us to determine interaction effects occur for the dependent variables. We used grand mean to center the independent variable to avoid problems with multicollinearity (Aiken & West, 1991). Teacher support was coded as 0 for the student group learning with the teachers (TS group) and 1 for the group learning without the teacher support (NTS group) to examine the presence of an interaction between the independent variable and teacher support. To conduct follow-up tests on significant interactions, we used simple slope analyses to examine whether there is significant difference between regressions lines at one standard deviation below and above mean (Aiken & West, 1991). In addition, we also used one-way ANOVA to test the significance between the with and without teacher support groups when the main effect of teacher support occurs, but no significant interaction effect.

Interaction effects: SRL as a Predictor

Model 1 for the dependent variable perceived autonomy had a significant R^2 , $R^2 = .20$, $F(2, 120) = 14.64$, $p < .001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of perceived autonomy, $p = .86$. In model 1, the main effect of teacher support was significant, $\beta = .36$, $t(119) = 4.44$, $p < .001$.

For the perceived competence, Model 1 had a significant R^2 , $R^2 = .11$, $F(2,120) = 7.70$, $p = .001$. There was a significant increase in R^2, showing that the interaction was a significant additional predictor of understanding ($\Delta R^2 = .35$, $F(1,119) = 77.12$, $p < .001$). In Model 2, the interaction effect was significant, $\beta = -.59$, $t(119) = -8.78$, $p < .001$. Figure 3 depicts the interaction between SRL and teacher support on perceived competence. The simple slope analyses revealed that at one standard deviation below, the group learning with the teachers benefited more than without the teachers, $\beta = .93$, $t(119) = 9.34$, $p < .001$; and at one standard deviation above, the group learning without the teachers benefited more than with the teachers, $\beta = -.27$, $t(119) = -2.63$, $p = .01$.

Model 1 for perceived relatedness had a significant R^2 , $R^2 = .28$, $F(2,120) = 24.25$, $p < .001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of perceived relatedness, $p = .83$. In model 1, the main effect of teacher support was significant, $\beta = .26$, $t(119) = 3.41$, $p = .001$.

For the intrinsic motivation, Model 1 had a significant R^2 , $R^2 = .11$, $F(2,120) = 7.27$, $p < .001$. There was significant increase in R^2, indicating that the interaction was a significant additional predictor of mental effort ($\Delta R^2 = .33$, $F(1,119) = 68.82$, $p < .001$).

In Model 2, the interaction effect was significant, $\beta = -.57$, $t(119) = -8.30$, $p < .001$. Figure 4 depicts the interaction between SRL and teacher support on intrinsic motivation. The simple slope analyses showed that at one standard deviation below, the group learning with the teachers benefited more than without the teachers, $\beta = .43$, $t(119) = 4.22$, $p < .001$; and at one standard deviation above, the group learning without the teachers benefited more than with the teachers, $\beta = -.67$, $t(119) = -6.74$, $p < .001$.

Interaction effects: DL as a Predictor

Model 1 for the dependent variable perceived autonomy had a significant R^2 , $R^2 = .17$, $F(2, 120) = 12.12$, $p < .001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of perceived autonomy, $p = .66$. In model 1, the main effect of teacher support was significant, $\beta = -0.36$, $t(119) = -4.36$, $p < .001$.

For the perceived competence, Model 1 had a significant R^2 , $R^2 = .07$, $F(2,120) = 4.36$, $p =.01$. There was a significant increase in R^2, showing that the interaction was a significant additional predictor of understanding ($\Delta R^2 = .36$, $F(1,119) = 73.06$, $p = .01$). In Model 2, the interaction effect was significant, $\beta = -.60$, $t(119) = -8.55$, $p < .001$. Figure 5 depicts the interaction between DLL and teacher support on perceived competence. The simple slope analyses revealed that at one standard deviation below, the group learning with the teachers benefited more than without the teachers, $\beta = .85$, $t(119) = 8.54$, $p < .001$; and at one standard deviation above, the group learning without the teachers benefited more than with the teachers, $\beta = -.34$, $t(119) = -3.42$, $p < .001$.

Model 1 for perceived relatedness had a significant R^2 , $R^2 = .21$, $F(2,120) = 15.53$, $p < .001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of perceived relatedness, p = .55. In model 1, the main effect of teacher support was significant, β = .27, t(119) = 3.25, p < .001.

For the intrinsic motivation, Model 1 had a significant R^2 , $R^2 = .06$, F(2,120) = 4.04, p = .02. There was significant increase in R^2, indicating that the interaction was a significant additional predictor of mental effort ($\Delta R^2 = .33$, F(1,119) = 64.08, p < .001). In Model 2, the interaction effect was significant, β = -.57, t(119) = -8.01, p < .001. Figure 6 depicts the interaction between DL and teacher support on intrinsic motivation. The simple slope analyses revealed that at one standard deviation below, the group learning with the teachers benefited more than without the teachers, β = .81, t(119) = 8.07, p < .001; and at one standard deviation above, the group learning without the teachers benefited more than with the teachers, β = -.34, t(119) = -3.43, p = .001.

Figure 4. The interaction between teacher support SRL on intrinsic motivation

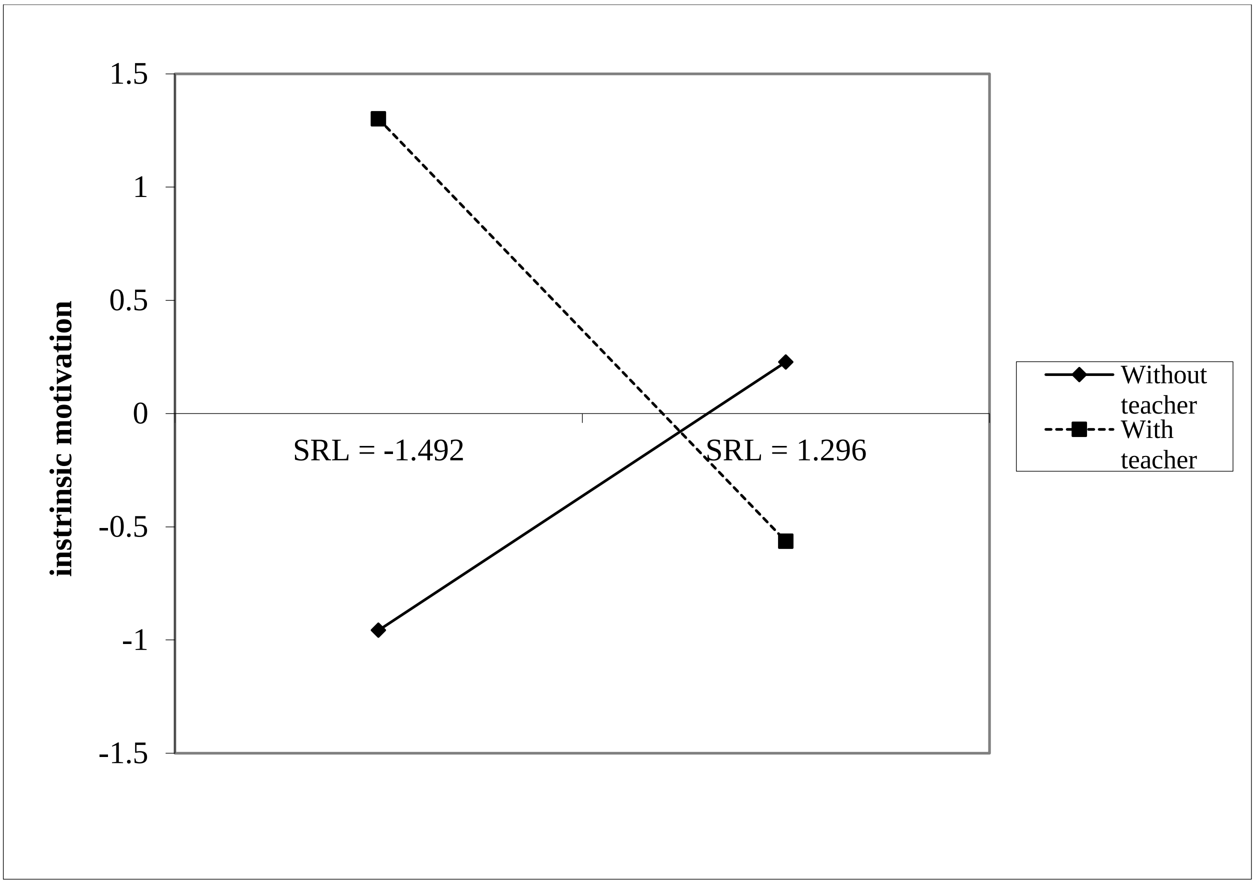


Figure 5. The interaction between teacher support and DL on perceived competence.

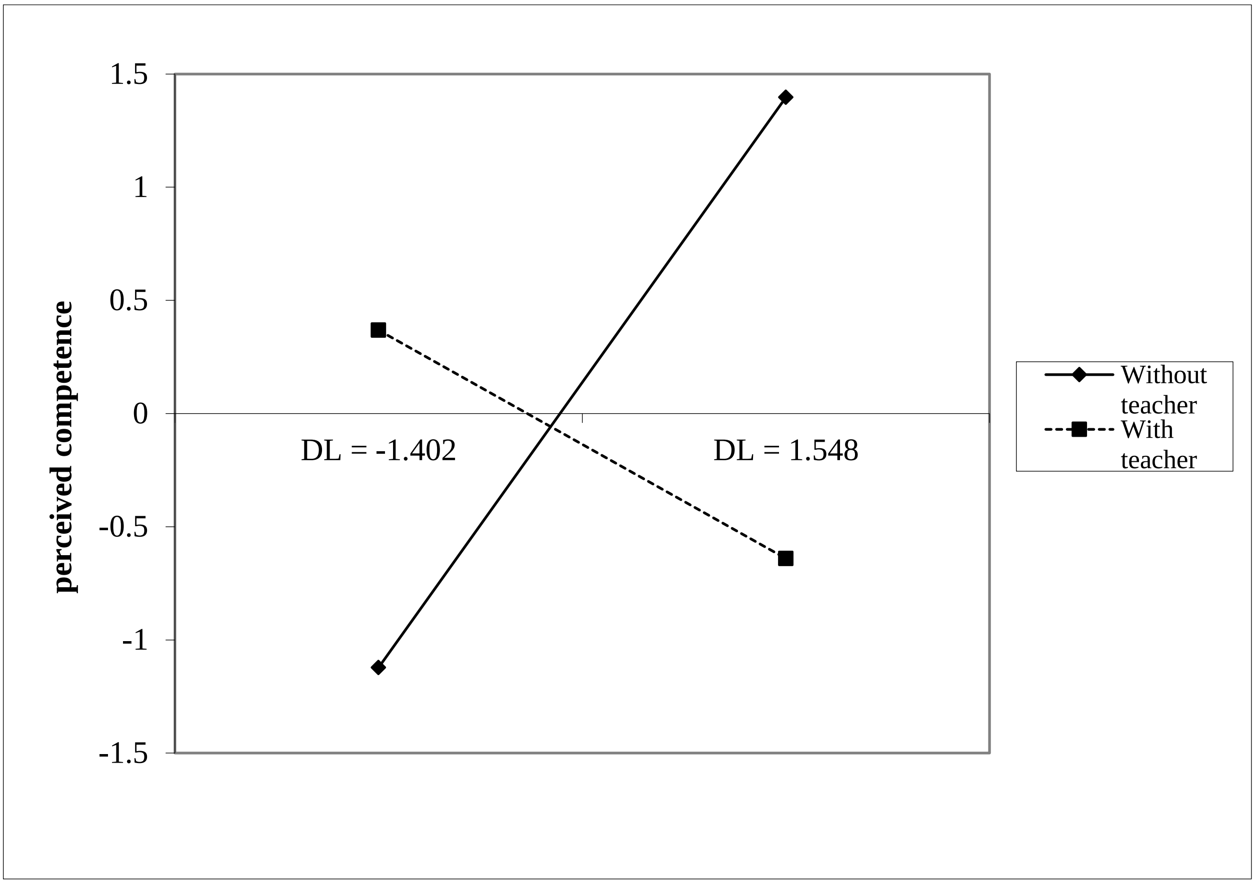
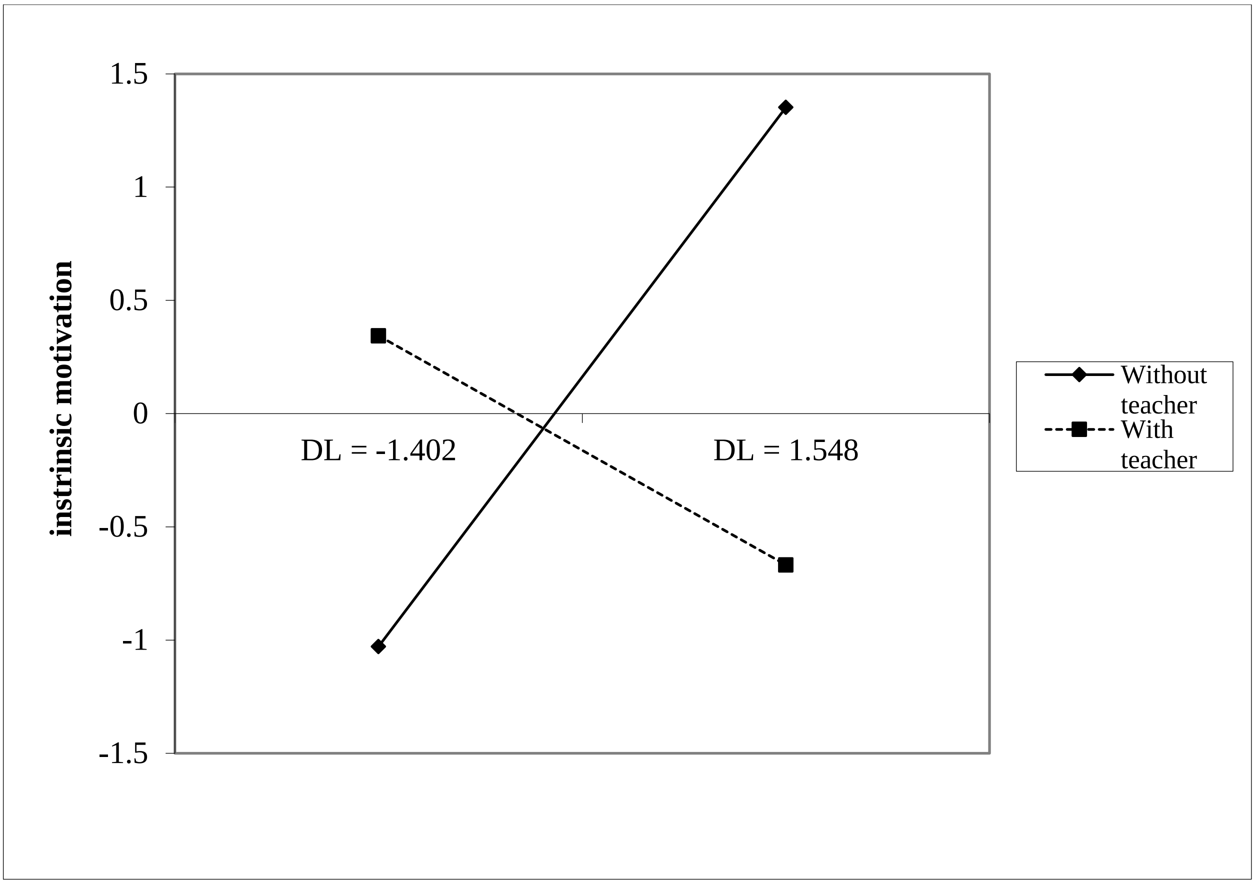


Figure 6. The interaction between teacher support and DL on intrinsic motivation.



Comparisons between the TS and NTS groups

As there were no interaction effects on perceived autonomy and relatedness, Follow-up ANOVAs indicated that the group learning with the teachers significantly perceived less autonomy ($F(1,121) = 18.98$, $p < .001$), but higher relatedness ($F(1,121) = 8.33$, $p < .01$) than the group learning without the teachers, and respectively.

Overall, the analyses indicated that (a) intrinsic motivation and competence to learn with the chatbot depended on both student expertise and teacher support; (b) the teacher support better satisfied the need for relatedness, and less satisfied the need for autonomy.

Discussions and Conclusions

The experiment reported in this paper was designed to investigate how teacher support moderates student expertise (i.e., either SRL or DL) and intrinsic motivation to learn with chatbots from the perspectives of needs satisfaction. This study aims to understand the role of AI technologies in student learning. Therefore, this paper presents four empirical implications, two theoretical contributions and three practical suggestions for both researchers, teachers and AI application developers.

Empirical implications

First, as predicted, student expertise and teacher support had an interaction effect on student intrinsic motivation to learn with the chatbot (H1). With the teacher support, the novice students perceived greater motivation than the advanced. In contrast, without teacher support, the novice students reported less motivation than the advanced students. These results suggest that the teacher support is more effective in motivating novice student learning with chatbot, which corroborates those of previous studies that examined how student expertise affects the effectiveness of instructional designs on motivation and learning (Chiu et al., 2020; Rey & Fischer, 2013). They are explained by Kalyuga' (2017) expertise reversal effect suggesting that instructional designs designed for novice students may not work well for advanced students. Instructional designs should be adjusted to cater student learning diversity. Moreover, this study confirmed that the novice students preferred to receive teacher support. The results showed that the novice students who received teacher support perceived greater intrinsic motivation than those novice students who did not receive support; while the advanced students had greater intrinsic motivation without teachers presences than those learning with their teachers. These results affirm those of Williamson and Eynon's (2020) and Shawar and

Atwell's (2007) studies that self-learning with chatbots is more likely to benefit motivated and high achieving students. A possible explanation is that the support from teachers (i.e., feedback and endorsement) helped the novice students better communicate with the chatbot but became more disturbing for the advanced students (Chong et al., 2018). The advanced students found teacher support redundant and needed no extra help when self-learning with the chatbot. In this case, they wanted greater self-learning time and saw teacher support as disruptions. Another plausible explanation is current machine learning in chatbots may not be advanced to generate conversations that help the novice adolescence to learn (Kolchenko, 2018; Shawar & Atwell, 2007). Most studies on learning with chatbots were conducted in higher education, i.e., university students are much more capable of learning with chatbots than K-12 education. This study shows that the current chatbots could be inadequately designed for less able or low achieving students. In addition, this interaction effect on motivation can be explained by the three needs – autonomy, competence and relatedness in SDT (Ryan & Deci, 2020).

In the second empirical implication, teacher support was the influential factor of autonomy and relatedness (H2). The analysis showed that the students felt more connected to the learning activities with the chatbot, but less freedom under teachers' presence and guidance (H3). The TS group had less control of how they spent their time using the chatbot, resulting in them feeling like they have less choices and senses of ownerships than the NTS group (H3). Teacher support created a more controlled or monitored learning environment that led students to feel a greater sense of embarrassment when interacting with the chatbot, for example they were careful to avoid misspelling words when being observed by teachers. This could reduce their willingness to take risks. Moreover, the TS group may feel more connected to the learning than the NTS group due to stronger teacher-student relationships (Chiu, 2022; Vansteenkiste et al., 2009). Interacting with a chatbot without human-human interaction reduces the sense of relatedness, particularly for adolescents. This may imply that the NTS group treats the self-learning with chatbots as homework and found it less connected to school learning.

The third empirical implication, similar to the first empirical implication, suggested that student expertise and teacher support had an interaction effect on competence toward learning with the chatbot (H1). The novice students in the TS group and the advanced students in the NTS group felt more capable and competent to make conversations with the chatbot. These results are also explained by the two reasons discussed in the first empirical implication.

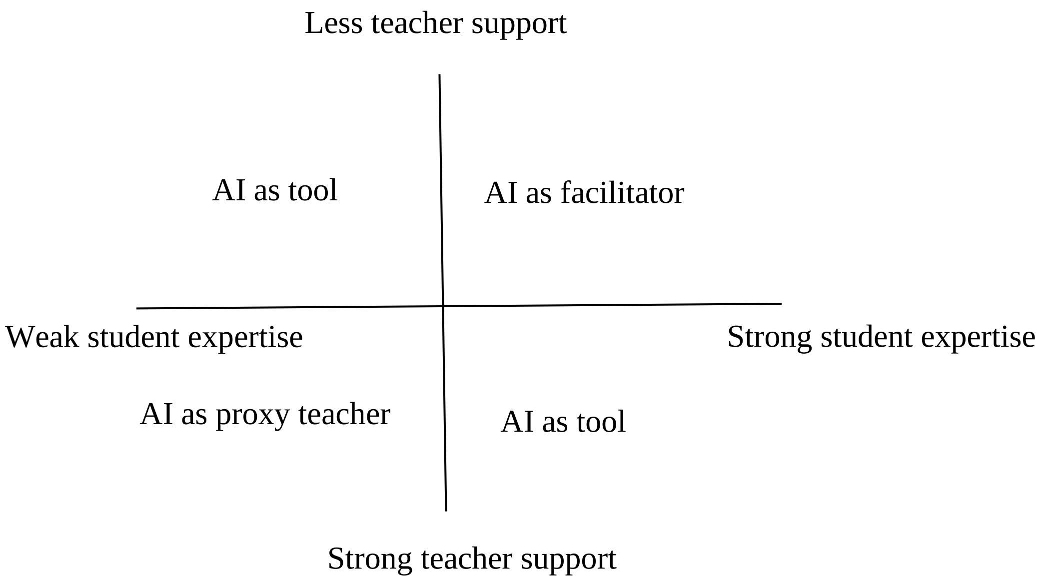
The final implication is derived by the above three implications. Need for competence was the most influential factor of intrinsic motivation to learn with the chatbot. According to SDT, the three needs – autonomy, competence and relatedness – work together to foster high-quality forms of motivation that, in-turn, lead to better engagement and persistence in activities (Ryan & Deci, 2020). Compare to the other two needs, satisfying competency is crucial in motivating student learning with the chatbot. This is aligned with most studies on behavioral intention to use technology (Sánchez-Prieto et al., 2017). These studies indicate that perceived self-efficacy positively predicts perceived ease of use and usefulness of new learning technology in practice, and negatively predicts anxiety toward learning with the technology. These findings reaffirm the importance of carefully designing the learning task with chatbots involving so as to support student competence (Bergdahl et al., 2020; Shawar & Atwell, 2007). Moreover, teacher played a moderating role in the relationships between student expertise and intrinsic motivation to learn with the chatbot. These findings indicated that the role of the chatbot depended on how competent students' perceived they are in SRL and DL. Optimal pedagogical effects may not be obtained without careful contextual considerations about the students characteristics and how these characteristics interplay with the machine. Given that these relationships have not yet been extensively explored and reported in past AI education research (Chiu, et al., 2022; Zawacki-Richter et al., 2019), these findings can fill these empirical gaps and further establish an underexplored empirical link between perceived needs and design of learning activities with AI. These findings can contribute useful insights into instructional design with AI.

Theoretical Contribution

The first theoretical contribution of this study lies in enriching the literature on AIEd by connecting it with needs satisfaction in SDT. The findings demonstrate that using needs satisfaction to explain the effects of teachers support and student expertise on intrinsic motivation to learn with AI technologies. Unlike most previous studies that examine motivation through the aggregated variable of the three needs satisfaction (Chiu, 2021a, 2022), this study attempts to understand how each of the needs satisfaction fosters student motivation. The needs satisfaction for competence appears to be one of the less influential factors in learning with AI, but its effects were increased in two conditions: the novice students with teacher support and the advanced student without teacher support. More importantly, the finding points to the importance of interpreting SDT in a contextual manner in which the three needs may interact differently given specific student characteristics. Such nuanced understanding may prevent dogmatic application of SDT to promote learning.

In second theoretical contribution, we propose three new notations "AI as facilitator", "AI as proxy teacher" and AI as tools, see Figure 7. "AI as facilitator" refers to the condition that students are able to collaborate with AI technologies for self-learning. In this condition, students work together with AI to solve problems, complete tasks, or learn new concepts. AI technologies actively engage students to process and synthesize information and concepts, rather than memorizing facts and figures. Moreover, “AI as proxy teacher” refers to the condition that students are able to self-learn with the technologies when needs support is provided. In this condition, students are not able to complete tasks by learning with AI technologies independently, and expect some external support for their innate needs, such as teacher or digital support (Chiu, 2021a, 2021b, 2022). AI technologies are proxy teachers that act as an intermediary for learning, and thus functions partially on behalf of teachers. They are helpful but insufficient for learning. In addition, “AI as tool” refers to the condition that students are not motivated to learn with AI and see them as normal tools, that can used to achieve a function, rather than an intelligent tools, that they can learn from interacting with.

Figure 7. Relationships between teacher support and student expertise



Practical Suggestion

We offer two practical suggestions for teachers and instructional designers, and one practical suggestion for educational technology developers. The first suggestion is that learning with AI as fully-automated activities may have detrimental effects on motivation, engagement and learning. Teachers should use SRL and DL as measures to determine the degree of self-learning in AI-based tasks and decide how to scaffold the learning when designing activities involving AI technologies such as chatbots, translations and graphics recognitions. For example, chatbots are a partner of learning through conversation. As conversation is discursive, structuring talk and conversations to design tasks with chatbots that requires less cognitive processing would be a good starting point for the novice and using open-ended talk would be better for the advanced (Teng & Zhang, 2018). The gist maps out the in between paths for diversity.

The other suggestion is that teacher support is still crucial in the fully-automated learning activities in K-12 education. Current AI-based chatbots cannot effectively cater for learners with different expertise levels because the school students are younger and their learning diversity are wider. As current chatbots need further refinement for successful learning (Smutny & Schreiberova, 2020), school students can get demotivated easier and their SRL is not sophisticated to overcome the problems they encountered (Peeters et al., 2016). In this case, the AI technologies can be facilitators, collaborator, teachers, or tools in learning for students with different characteristics.

Final, the results of this study further suggest AI makes the educational technologies more intelligent but their quality of student-generated data and leaning algorithm affect students learning experiences. If data are scarce or algorithm are not advanced, the benefits of chatbots are minimal. Motivated, persistent and advanced students tend to have better learning experiences. This could potentially increase the gap between low achieving and high achieving students (Kolchenko, 2018). We encourage AI application developers to take student expertise into account when training models in educational chatbots. These models are more authentic and realistic that may fit better with the human dominated pedagogical context, which will improve the performance of educational chatbots.

Limitations and Future directions

There are limitations in this study and six are noted here. First, this study appears to support the effects of student expertise and teacher support on intrinsic motivation and needs satisfaction. However, to validate the finding, the scope of the present experiment could be extended to include different types of engagement (e.g., behavioral, cognitive and emotional, and social) or on different student expertise (e.g., prior knowledge, AI learning experience). Second, there might have been a gap between students' perception of needs satisfaction and their actual performance of these skills. More studies adopting objective measures, such as learning performance and achievement, are suggested. Third, ongoing learning process measures, such as change in needs satisfaction and performance in different phases were not included in this study. Longitudinal design that tracks student learning process is suggested to be adopted for future research. Fourth, in this study, the chatbot was developed for commercial application, although this adds to the authentic nature of the task, it may not reveal the effectiveness of chatbot specially designed for education. Future studies should investigate education-focused chatbots. The final limitation is that the experiment was conducted over different sessions. Environmental factors, for example, time and weather, may influence student motivation for learning, which lead to differences between conditions. Future studies should use parallel sessions for the experiment.

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