A Self-determination Theory (SDT) Design Approach for inclusive and diverse Artificial Intelligence (AI) Education

First draft

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The introduction of artificial intelligence (AI) as a subject in K-12 education is a new and important global strategic initiative, but there is a serious lack of studies in relation to this initiative that address inclusion and diversity of education. Self-determination theory (SDT) can explain student engagement from the needs satisfaction perspective. Therefore, this project aimed to investigate how SDT-based needs support by teachers and student attributes (gender and achievement level) affect AI learning at secondary school level. It adopted a two-study design, with each study using a 2 x 2 between-subjects factorial design with student needs support from teachers as one factor and one of the student attributes as the other: gender in Study 1 and achievement level in Study 2. In both studies, there were two groups – SDT-based (teacher needs support) and control (without). The analyses revealed that in the SDT-based program, (1) the students had a more positive perception of AI learning and felt that their needs were satisfied, and (2) there were non-significant differences in AI learning between boys and girls and between high and low achievers. The findings suggest that a focus on needs satisfaction could engage boys and girls, and high and low achievers in AI learning. As they become more engaged, they are likely to gain more confidence, feel that the content is more relevant, and become intrinsically motivated to pursue further AI learning.

Keywords: AI education, K-12 education, inclusion, diversity, self-determination

theory, motivation

Nations across the globe are developing strategic initiatives to equip future generations with the skills and knowledge needed to thrive in the digital age (Touretzky et al., 2019). Among these initiatives are research and education projects instigated by governments, universities, and schools in many countries and regions, including Australia, China, Europe, India, Singapore, Thailand, and the United States, to introduce the topic of artificial intelligence (AI) into the formal K–12 curriculum. These projects, undertaken in response to AI increasingly permeating people's everyday lives, have delivered crucial findings for the development of AI education, providing suggestions for key content, curriculum frameworks, and assessment items.

As AI skills and knowledge quickly become integral parts of a holistic education, it is essential to address the issue of equity (Chiu et al., 2021). UNESCO states that a high-quality school education should be designed in a fair and inclusive manner that enables all students to acquire and develop the knowledge, skills, and values that contribute to a meaningful and productive life (Stabback, 2016). In schools, most of the engineering curriculum, which forms part of the STEM group of subjects (science, technology, engineering, and mathematics), has been conducted after formal lessons and outside of normal classroom settings. As most participants have been high-achieving boys, the subject suffers from a lack of diversity that has created issues of inclusion and equity.

Inclusion and diversity, which are important to ensure the success of AI education (Delaine et al, 2016; Ibe et al., 2018), are primarily achieved by increasing the motivation and engagement of underrepresented groups in learning (Chiu & Lim, 2020; Chiu & Mok, 2017; Chiu et al., 2020; Eccles, 2007; Prince & Hadwin, 2013). Formal school education heavily relies on how teachers design and deliver learning activities (Kelly, 2009). Instructional designs that address inclusion and diversity can motivate student engagement by catering to different needs (Chiu & Lim, 2020; Chiu & Mok, 2017; Chiu et al., 2020). According to self-determination theory (SDT), student engagement and well-being are promoted by satisfying three basic psychological needs: autonomy, competence, and relatedness. Therefore, teachers whose learning activities satisfy these three needs can engage more girls and low-achieving students in learning AI. Moreover, interdisciplinary research – adding psychological perspectives to engineering education research – advances diverse and inclusive engineering education practices (Baillie et al., 2011).

There have been no SDT-based studies into the promotion of inclusion and diversity in K-12 AI education to date. In the literature on inclusion and diversity in general engineering education, most studies have suggested using female mentors and role models and adopting more project- and team-based learning styles to engage girls and low-achieving students. The present study looks at the issue from the different perspective of needs satisfaction by investigating whether having teachers support student needs can promote inclusion and diversity in AI education. As teaching AI is new to schools, more studies are needed to inform researchers, government officers, and practitioners to design, develop, and evaluate quality learning and teaching activities (Chiu, 2020, 2021a; Chiu et al., 2021; Pedró et al., 2019).

Literature Review

AI Education in K–12

AI is recognized as an ever-changing field with a diverse range of topics that extend beyond computational thinking (Chiu et al., 2021). Not only does AI comprise a variety of sub-fields, such as natural language processing and neural networks, but it also explores such broader skills as critical thinking, meaning-making, evaluating, and troubleshooting (Chiu, 2021a; Chiu et al., 2021). Due to the breadth of topics and wide range of skills in the AI field, it is challenging to design and implement a coherent AI curriculum for K–12 without deliberate research and planning (Chiu & Chai, 2020). The first study was Papert and Solomon's (1971) exploration of young students learning AI with turtle robots and Logo programming. A half-century later, AI teaching has become an emerging area of educational research, with a range of projects promoting AI education at the K–12 level carried out by universities internationally. Three examples are as follows. First, a notable collaboration between SenseTime and East China Normal University led to the publication of the first AI textbook series for high school students, *Fundamentals of Artificial Intelligence* (SenseTime, 2018). The series is most suitable for academically competent students or those with strong engineering backgrounds, and the content fosters the development of technical knowledge and skills in AI. Second, Massachusetts Institute of Technology (MIT) examined various hands-on robot learning activities and focused on the design of the students' learning process (Williams et al., 2019). The MIT study provided insights into the use of robotics in the learning of AI but also raised concerns about gender-biased lesson designs, which seemed to favor boys and neglect the interests of girls. Third, The Chinese University of Hong Kong collaborated with local schoolteachers to develop a set of AI teaching resources for middle schools and examined the effectiveness of these resources on improving students' AI knowledge and attitudes (Chiu et al., 2021). However, this project did not investigate whether these resources addressed issues of inclusion and diversity.

Governments in different regions have also initiated national education policies for AI. Chiu and colleagues (2021) reviewed AI education policies in different countries. Korea and the United States (with the AI4K12 project) both developed national curriculum standards to guide schools and teachers to design teaching activities for AI; the European Union has provided the public (including young children) with free resources and courses to acquire AI knowledge and skills; in India, the Central Board of Secondary Education adopted the Microsoft K12 education transformation framework to develop their school curriculum for Grade 9 students. These projects have identified and suggested essential content knowledge and concepts (e.g., ethics, machine learning, and AI applications), but have not addressed the issues surrounding equity and inclusion. In summary, although the work of universities and education departments has identified key content and activities for teaching AI in schools, there is no K–12 AI program designed with inclusion and diversity as a priority. More work is needed to instill AI education with these essential attributes (Chiu et al., 2021; Delaine et al, 2016; Ibe et al., 2018).

However, UNESCO states that a quality education should be designed in a fair and inclusive manner to enables all students to acquire and develop the knowledge, skills and values, which leads to meaningful and productive lives (Stabback, 2016). More work is needed to cultivate inclusion and diversity in AI education (Chiu et al., 2021; Delaine et al, 2016; Ibe et al., 2018).

Inclusion and Diversity in School Engineering Education

AI is often seen as an engineering discipline. Engineering education is primarily offered as a subject at the post-secondary level and mostly to high-achieving male students, leaving girls and less able students underrepresented (Delaine et al, 2016; Ibe et al., 2018). The subject is thus relatively lacking in inclusion and diversity (DuBow et al., 2016). Catching student interest early then following through with that interest at the K–12 level may be the key to inspiring more students, particularly from underrepresented groups, to pursue engineering or engineering-related study and/or careers (Delaine et al., 2016; Ibe et al., 2018). The provision of engineering-related learning activities in schools has recently increased, with the rising popularity of STEM subjects. However, without appropriate pedagogies, engagement in these activities may simply mirror the disparities observed at the post-secondary level (Baillie et al., 2011; Delaine et al., 2016). Accordingly, the teaching of engineering-related subjects, such as AI, at the K–12 level represents a new global trend in education that needs further research, particularly regarding inclusion and diversity.

The literature has suggested that in schools there are differences in attitudes toward engineering between girls and boys and between students at high and low levels of ability (Delaine et al., 2016; Roehrig et al., 2012). Studies have found that girls and less able students have less interest, competence, and confidence in their engineering skills and place less intrinsic value on such skills. Female engineering majors generally possess fixed mindsets that engineering activities are designed for men, which results in underperformance (Heyman et al., 2002). A plausible reason for this mindset is students' perceptions that the teaching and learning activities are not fully inclusive (Ibe et al., 2018). Girls and less able students feel less supported and comfortable than their high-achieving male counterparts when engaging in these activities. For example, the use of robots for learning AI is not gender-neutral and favors boys, while the heavy emphasis on coding activities may be too challenging for less able students. Moreover, most engineering-related activities in the K–12 curricula are conducted outside of the classroom setting. Some of the activities are designed to train students to join external competitions; in these cases, students who participate in the activities are generally perceived to be high achievers. Furthermore, Archer et al. (2010) found that school students were deterred in the pursuit of STEM education by their impressions of the generally high academic standards of university science and engineering students. These stereotypes produce negative attitudes toward engineering that translate into higher drop-out rates among girls and poor performing students (Bøe et al., 2011). It is all too often the case that students are excluded on grounds of their socio-economic circumstances, gender, or academic ability.

To meet UNESCO's sustainable development goals of quality education, good quality K–12 teaching needs to be inclusive and diverse to assist all students, regardless of their socio-economic background, gender, or academic ability, to develop their capabilities to the fullest (Stabback, 2016). Every child is different, not all are academically gifted, and some will do better in one field than in another; but all children should be supported and encouraged to achieve their potential. Therefore, a high-quality AI curriculum for K–12 should make space for teachers to recognize each student's personal and cognitive capacities and to support students' needs (Chiu, 2020, 2021a; Chiu & Chai, 2020; Lennert da Silva & Mølstad, 2020). Teachers should respect differences in the ways children learn, encourage learning differentiation, and ensure that the design and delivery of learning activities are appropriate to their students' needs and capabilities. Moreover, using interdisciplinary research advances diverse and inclusive engineering education practices (Baillie et al., 2011), and this project add psychological domain (SDT) to engineering education.

SDT and Student Motivation

SDT provides a theoretical framework for motivation that has strong implications for both classroom practice and educational reform policies (Ryan & Deci, 2017, 2020). The theory posits that all individuals possess three basic psychological needs—autonomy, relatedness, and competence—that motivate self-initiated behavior and engagement (Ryan & Deci, 2017, 2020). According to SDT, teachers can motivate student engagement by satisfying their needs. When their three basic needs are satisfied, students' motivational orientation can move along a continuum, from amotivation to extrinsic motivation to intrinsic motivation, as students increasingly internalize their motivation until something intrinsic about the activity drives them. This intrinsic motivation sustains students' personal growth and well-being, potentially enhancing learning outcomes. Accordingly, when teaching and learning meet the needs for autonomy, competence, and relatedness, students with any motivation orientation are more likely to be intrinsically motivated to learn.

Teachers can support student needs by encouraging student autonomy (autonomy), providing for learning (competence), and being involved interpersonally (relatedness) (Lietaert et al., 2015; Sierens et al., 2009). Autonomy-supportive teachers will encourage and facilitate students to pursue their own learning goals and endorse students' choices of behaviors and learning approaches in the classroom (Assor et al., 2002; Chiu, 2021b, 2021c, 2021d). For example, they allow for choices over learning activities and materials, give reasons when choices are limited, and avoid using controlling and demanding language (Katz & Assor, 2007; Chiu, 2021b, 2021c). If students make their own decisions based on their personal goals, interests, and abilities, they feel empowered in learning.

Competence-supportive teachers will provide clear and specific guidance for learning, delineate the boundaries of learning activities, express confidence in students' abilities, give learning-relevant feedback (Chiu, 2021b, 2021c), and provide well-designed learning materials (Chiu et al., 2020; Chiu & Mok, 2017). Students will develop a sense of mastery and feel challenged in their learning and encouraged to actively participate in learning activities.

Relatedness-supportive teachers will develop close and caring teacher–student and student–student relationships by creating and maintaining warm, affectionate, and joyful learning environments (Chiu, 2021b, 2021c; Skinner et al., 2008). They will provide students with emotional support (e.g., caring, acceptance, and assistance) (Vollet et al., 2017). Feeling safe and welcome, and connected to their school and subjects, and developing strong personal networks that can provide help and support, leads students to greater learning engagement (Ryan & Deci, 2017; Chiu, 2021b, 2021c). Accordingly, students of different genders and ability levels will be more engaged in learning when their three needs are satisfied.

Method

Research Design

Based on SDT, student needs support from teachers has been widely applied to optimize student learning in the classroom and online contexts (e.g., Ruzek et al., 2016; Standage et al., 2005; Chiu 2021a, 2021b). However, to the best of our knowledge, very few or no SDT-based studies have investigated how needs support promotes inclusion and diversity in AI (or engineering more generally) education. Boys and girls and high and low achievers seem to have different attitudes toward AI learning. Moreover, adding psychological needs to engineering education research (interdisciplinary research) can advance diverse and inclusive engineering education practices (Baillie et al., 2011). The goal of this project was to adopt the perspective of needs satisfaction to investigate how SDT-based needs support and student attributes (gender or achievement level) affect AI learning in a K–12 setting. More specifically, the study examined whether needs support from teachers can improve AI learning—readiness, attitude, confidence, anxiety, and intrinsic motivation—and cater to (i) boys and girls and (ii) strong and weak coding skill levels. Accordingly, the following three research questions were examined:

RQ1: What is the influence of needs support from teachers on AI learning for students of different genders and achievement levels?

RQ2: What is the influence of needs support from teachers on needs satisfaction for students of different genders and achievement levels?

RQ3: Does needs support from teachers improve students' AI learning?

The findings of this project could contribute to the design of K–12 engineering education, bring large numbers of students, regardless of their gender and achievement levels, into contact with AI and engineering, and boost the confidence, ease the anxiety, and enhance the attitude and motivation of students toward the subject. More young students will then be prepared to grasp opportunities in post-secondary education and the job market in engineering-related disciplines.

This project adopted a two-study design, with each study using a 2 × 2 between-subjects factorial design with student needs support from teachers as one factor and one of the student attributes as the other: gender in Study 1 and achievement level in Study 2. This approach is supported by its use in studies with similar goals (e.g., Chiu, 2021c; Du et al., 2020; Hiemstra et al., 2015; Schneider et al., 2018).

Study 1

Participants and Procedure

The participants in Study 1 were 64 male and 64 female Grade 9 students from three different schools (with a mean age of 14.5 years), and eight teachers with extensive teaching experience in Computer Science. The teachers attended two 3-hour workshops on SDT-based needs support. The students were then divided into two groups: an SDT-based group and a control group to be exposed to normal teaching strategies ("business as usual"). There were 32 male and 32 female students in each group. The students participated in a 15-day (42-hour) summer AI program. Fifteen-minute pre- and post-test questionnaires were administered to the students on the first and last day of the program, respectively. Each group was taught by four teachers.

The AI Program

The AI program was designed using the curriculum framework suggested by Chiu (2021a), as shown in Figure 1. There were three main topics: What is AI? (Knowledge); How does AI work? (Process); and What are the impacts of AI? (Impact). The students attended five 1-hour lectures and completed a project in groups of five or six. The strategies for teachers to provide needs support were designed using the SDT-based studies of Chiu (2021b, 2021c). The instructional strategies of the two groups were as follows.

In the SDT-based group, to foster autonomy, the teachers took the students' perspective, embedded autonomy in the learning activities, and used invitational language. The students determined the problem they wanted to study and initiated their own projects. In devising solutions, they decided the form of their prototypes (e.g., application, hardware, proposal, or essay) and what tools (e.g., teachable machine, AIY Voice Kit from Google, Huskylen, or drone) to use. To satisfy the need for competence, the teachers explained to the students how they could make progress and achieve the desired outcomes in structured learning activities. They communicated clear expectations and offered step-by-step guidance. To support relatedness, the teachers supported emotional connections by fostering interpersonal relationships. They formed student groups by matching students together with others who had similar self-identified problems and conducting daily teacher–student group meetings. Furthermore, the problems addressed in student projects were under the theme “AI for social good,” with the students creating solutions to benefit communities.

In the control group, the teachers used the existing—more controlling—teaching strategies. They told the students what to do and assigned a specific project topic—a robot car that can avoid obstacles—to the students. The teachers allowed the students to use a Raspberry Pi only as a tool (less autonomy) and explained their expectations and offered one-off guidance to the students in the first lesson only (less competence). Moreover, the teachers randomly divided the students into groups, conducted only whole-class meetings for every lesson, and assigned a project topic that was not for the benefit of the wider community (less relatedness).

Participant Questionnaire

Apart from demographic data, the pre- and post-program questionnaires included items collecting data for two categories of variables: AI learning (perceived AI readiness (AID), AI confidence (AIC), AI attitude (AIAT), AI anxiety (AIAX), and intrinsic motivation to learn AI (AIIM)) and needs satisfaction (perceived autonomy, competence, and relatedness). Each of the variables was measured using four items rated on a 5-point Likert scale (1- strongly disagree; 5- strongly agree) and adapted from previous studies with acceptable reliability and validity.

Measures of AI learning

AIRD refers to the perceived level of comfort in the daily use of various AI technologies. Students with stronger perceptions were more likely to adopt new AI applications in their everyday life. The items were adapted from the studies of Chai et al. (2021) and Chiu et al. (2021), with acceptable reliability ($\alpha = .89$) in similarly aged groups. The four items were “I prefer to use the most advanced AI technologies”; “I am confident that AI technologies will follow my instructions”; “AI technologies give people more control over their own lives”; and “Applications and services that use the latest AI technologies are much more convenient to use.”

AICF measures perceived confidence in learning AI content. The items were adapted from the studies of Chai et al. (2021) and Chiu et al. (2021), in which they had a reliability of $\alpha = .91$. The four items were “I am confident that I can succeed if I work hard enough in learning AI”; “I am certain that I can learn the basic concepts of AI”; “I am certain that I can understand the most difficult AI resources”; and “I am certain that I can design AI applications.”

AIAX refers to the perceived anxiety level toward learning AI and was measured using items adapted from the study of Wang and Wang (2019), in which the reliability was $\alpha = .97$. The items were “Learning to understand all of the special functions associated with an AI technique/product makes me anxious”; “Learning to use AI techniques/products makes me anxious”; Learning how an AI technique/product works makes me anxious”; “Learning to interact with an AI technique/product makes me anxious.”

AIAT measures attitude toward AI. The four items used in this study were adapted from the study of Chiu (2017), in which the reliability was $\alpha = .87$. The items were “I look forward to using AI in my daily life”; “I think it would be very wise to use

AI in my daily life"; "I would like to use AI in my learning"; "I think it would be very wise to use AI in my learning."

AIIM was measured by four items adapted from the study of Chiu et al. (2021), in which the reliability was α = .92. The items were "I enjoy learning AI very much"; "I found learning AI fun"; "I would describe AI learning as very interesting"; "Learning AI holds my attention well."

Measures of Perceived Needs Support from Teachers

Perceived needs support from teachers measures the student needs satisfaction for autonomy, relatedness, and competence as facilitated by their teachers in the program. All of the items were adapted from previous studies conducted with British children by Standage and colleagues (2005) and validated for Hong Kong school students by Chiu (2021a, 2021b). The four items for perceived autonomy support, with an original reliability of α = .80, were "When my teacher teaches the program, I have a say regarding what skills I want to learn"; "When my teacher teaches the program, I can decide which activities and tools I want to learn"; "When my teacher teaches the program, I have some choice in what I want to learn"; and "When my teacher teaches the program, I feel free to express myself, my opinions, and my concerns in AI learning." The items for perceived competence support, with an original reliability of α = .84, were "My teacher makes me feel like I am good at learning"; "I feel that my teacher likes us to do well"; "My teacher makes me feel like I am able to do the activities in class"; and "My teacher makes me feel pretty confident about learning AI." The items for perceived relatedness support, with an original reliability of α = .87, were "When learning in the AI program, I feel supported"; "When learning in the AI program, I feel close”; “When learning in the AI program, I feel valued”; and “When learning in the AI program, I feel it is relevant to me.”

Analytical Approach and Descriptive Statistics

To answer RQ1, analyses of covariance (ANCOVAs) were conducted to assess the differences between groups in post-program mean scores after accounting for pre-program learning scores; to answer RQ2, analyses of variance (ANOVAs) were conducted to compare needs satisfaction; to answer RQ3, paired *t*-tests were performed to analyze differences between pre- and post-program scores. Table 1 presents the descriptive statistics for all variables. All variables met the assumption of homogeneity of variance, with Levene’s test returning $p > .05$ for all analyses.

To answer RQ1, with regard to AIRD, the results of univariate ANCOVAs showed that there was a significant main effect of needs support from teachers, $F(1,123) = 23.51$, $p < .001$, partial $\eta^2 = .16$, a significant main effect of gender, $F(1, 123) = 19.73$, $p < .001$, partial $\eta^2 = .14$, and a significant interaction effect, $F(1, 123) = 12.45$, $p = .001$, partial $\eta^2 = .09$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = .47$, $p = .50$, partial $\eta^2 = .01$, a significant simple effect for the control group that boys learned better than girls, $F(1, 61) = 26.27$, $p < .001$, partial $\eta^2 = .30$, no simple effect for boys, $F(1, 61) = .61$, $p = .44$, partial $\eta^2 = .01$, and a significant simple effect that girls with SDT-based support learned better than those without, $F(1, 61) = 19.60$, $p < .001$, partial $\eta^2 = .45$.

The analyses also revealed that for AICF, there was a significant main effect of needs support from teachers, $F(1,123) = 20.63$, $p < .001$, partial $\eta^2 = .14$, a significant main effect of gender, $F(1, 123) = 15.24$, $p < .001$, partial $\eta^2 = .11$, and a significant interaction effect, $F(1,123) = 7.28$, $p = .008$, partial $\eta^2 = .06$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 1.14$, $p = .29$, partial $\eta^2 = .02$, a significant simple effect for the control group that boys learned better than girls, $F(1, 61) = 17.15$, $p < .001$, partial $\eta^2 = .22$, no simple effect for boys, $F(1, 61) = 1.34$, $p = .25$, partial $\eta^2 = .02$, and a significant simple effect that girls with SDT-based support learned better than those without, $F(1, 61) = 32.27$, $p < .001$, partial $\eta^2 = .35$.

With regard to AIAT, the analyses revealed a significant main effect of needs support from teachers, $F(1,123) = 23.84$, $p < .001$, partial $\eta^2 = .16$, a significant main effect of gender, $F(1, 123) = 13.35$, $p < .001$, partial $\eta^2 = .10$, and a significant interaction effect, $F(1,123) = 5.72$, $p = .01$, partial $\eta^2 = .04$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = .90$, $p = .35$, partial $\eta^2 = .01$, a significant simple effect for the control group that boys learned better than girls, $F(1, 61) = 14.70$, $p < .001$, partial $\eta^2 = .19$, no simple effect for boys, $F(1, 61) = 2.81$, $p = .10$, partial $\eta^2 = .04$, and a significant simple effect that girls with SDT-based support learned better than those without, $F(1, 61) = 34.42$, $p < .001$, partial $\eta^2 = .36$.

With regard to AIAX, the analyses revealed a significant main effect of needs support from teachers, $F(1,123) = 4.61$, p =.03, partial $\eta^2 = .04$, a significant main effect for gender, $F(1, 123) = 20.39$, $p < .001$, partial $\eta^2 =0.14$, and a significant interaction effect, $F(1,123) = 6.76$, $p = .01$, partial $\eta^2 = .05$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 2.03$, $p = .16$, partial $\eta^2 = .03$, a significant simple effect for the control group that boys learned better than girls, $F(1, 61) = 22.81$, $p < .001$, partial $\eta^2 = .27$, no simple effect for boys, $F(1, 61) = .09$, $p =$

.77, partial $\eta^2 = .001$, and a significant simple effect that girls with SDT-based support learned better than those without, $F(1, 61) = 9.61$, $p = .003$, partial $\eta^2 = .14$.

With regard to AIIM, the analyses revealed a significant main effect of needs support from teachers, $F(1,123) = 26.00$, $p < .001$, partial $\eta^2 = .17$, a significant main effect of gender, $F(1, 123) = 19.29$, $p < .001$, partial $\eta^2 =0.14$, and a significant interaction effect, $F(1,123) = 7.54$, $p = .007$, partial $\eta^2 = .06$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 1.98$, $p = .16$, partial $\eta^2 = .03$, a significant simple effect for the control group that boys learned better than girls, $F(1, 61) = 19.31$, $p < .001$, partial $\eta^2 = .24$, no simple effect for boys, $F(1, 61) = 2.17$, $p = .15$, partial $\eta^2 = .03$, and a significant simple effect that girls with SDT-based support learned better than those without, $F(1, 61) = 34.19$, $p < .001$, partial $\eta^2 = .36$.

To answer RQ2, with regard to perceived needs satisfaction, the analyses revealed that there was a significant main effect of support for autonomy, $F(1,124) = 74.78$, $p < .001$, partial $\eta^2 = .38$, competence, $F(1,124) = 74.30$, $p < .001$, partial $\eta^2 = .38$, and relatedness $F(1,124) = 50.12$, $p < .001$, partial $\eta^2 = .29$. A significant main effect was found for gender in autonomy, $F(1,124) = 10.70$, $p = .001$, partial $\eta^2 = .08$, competence, $F(1,124) = 6.33$, $p = .01$, partial $\eta^2 = .05$, and relatedness, $F(1,124) = 6.69$, $p = .01$, partial $\eta^2 = .05$. No significant interaction effect was found for autonomy, $F(1,124) = .77$, $p = .38$, partial $\eta^2 = .01$, competence, $F(1,124) = 2.47$, $p = .12$, partial $\eta^2 = .02$, or relatedness, $F(1,124) = .292$, $p = .59$, partial $\eta^2 = .02$. The results of follow-up analyses showed that the SDT-based group perceived greater autonomy, competence, and relatedness than the control group, $F(1,127) = 69.56$, $p < .001$, $F(1,127) = 70.50$, p $< .001$, and $F(1, 127) = 48.21$, $p < .001$, respectively. The analyses also showed that boys perceived greater autonomy, competence, and relatedness than girls, $F(1,127) = 6.75$, $p = .01$, $F(1, 127) = 3.98$, $p = .04$, and $F(1,127) = 4.83$, $p = .03$, respectively.

To answer RQ3, the analyses revealed that boys and girls in the SDT-based group improved in readiness (boys: $t(31) = 8.82$, $p < .001$; girls: $t(31) = 5.71$, $p < .001$), confidence (boys: $t(31) = 6.94$, $p < .001$; girls: $t(31) = 5.79$, $p < .001$), attitude (boys: $t(31) = 8.85$, $p < .001$; girls: $t(31) = 6.18$, $p < .001$), and intrinsic motivation to learn AI (boys: $t(31) = 8.53$, $p < .001$; girls: $t(31) = 8.00$, $p < .001$), and reduced their anxiety (boys: $t(31) = 3.00$, $p = .005$; girls: $t(31) = 2.86$, $p < .001$).

It can be concluded, see Table 2, that the SDT-based program did not result in significant differences between boys and girls across the measures of AI learning and performed significantly better in satisfying the three needs (RQ2). Regardless of gender, the SDT-based program significantly enhanced students' perceived AI learning: AIRD, AICF, AIAT, AIAX, and AIIM (RQ3).

Study 2

Method

Participants and Research Procedure

Study 2 adopted the same research design as Study 1, with the same AI program and questionnaire, but with different student participants. For Study 2, the participants were 127 Grade 9 students from three schools, of which 64 were high achievers in coding and 63 were low achievers. The mean age was 14.5 years. The student participants were given a coding (Scratch) pre-task involving the concepts of selection and iteration to complete in 30 minutes. Those who completed the task without errors were considered high achievers. Following this pre-task, there were 32 high and 32 low achievers in the SDT-based group, and 32 high and 31 low achievers in the control group.

Results

Table 3 presents the descriptive statistics for all variables. All variables met the assumption of homogeneity of variance, with Levene's test returning $p > .05$ for all analyses.

To answer RQ1, with regard to AIRD, the analyses showed that there was a significant main effect of needs support from teachers, $F(1,122) = 12.54$, $p = .001$, partial $\eta^2 = .09$, a significant main effect of achievement, $F(1, 122) = 27.43$, $p < .001$, partial $\eta^2 = .18$, and a significant interaction effect, $F(1, 122) = 15.81$, $p < .001$, partial $\eta^2 = .12$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 3.11$, $p = .08$, partial $\eta^2 = .05$, a significant simple effect in the control group that high achievers learned better than low achievers, $F(1, 60) = 29.55$, $p < .001$, partial $\eta^2 = .33$, no simple effect for high achievers, $F(1, 61) = .07$, $p = .80$, partial $\eta^2 = .001$, and a significant simple effect that low achievers with SDT-based support learned better than those without, $F(1, 60) = 25.88$, $p < .001$, partial $\eta^2 = .30$.

With regard to AICF, the analyses showed that there was a significant main effect of needs support from teachers, $F(1,122) = 10.75$, $p = .001$, partial $\eta^2 = .08$, a significant main effect of achievement, $F(1, 122) = 28.60$, $p < .001$, partial $\eta^2 = .20$, and a significant interaction effect, $F(1, 122) = 16.54$, $p < .001$, partial $\eta^2 = .12$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 1.39$, $p = .24$, partial $\eta^2 = .02$, a significant simple effect in the control group that high achievers learned better than low achievers, $F(1, 60) = 44.97$, $p < .001$, partial $\eta^2 = .43$, no simple effect for high achievers, $F(1, 61) = .31$, $p = .58$, partial $\eta^2 = .01$, and a significant simple effect that low achievers with SDT-based support learned better than those without, $F(1, 60) = 28.35$, $p < .001$, partial $\eta^2 = .32$.

With regard to AIAT, the analyses revealed that there was a significant main effect of needs support from teachers, $F(1,122) = 11.97$, $p = .001$, partial $\eta^2 = .09$, a significant main effect of achievement, $F(1, 122) = 29.25$, $p < .001$, partial $\eta^2 = .19$, and a significant interaction effect, $F(1, 122) = 16.97$, $p < .001$, partial $\eta^2 = .12$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 2.99$, $p = .09$, partial $\eta^2 = .05$, a significant simple effect in the control group that high achievers learned better than low achievers, $F(1, 60) = 36.26$, $p < .001$, partial $\eta^2 = .38$, no simple effect for high achievers, $F(1, 61) = .30$, $p = .59$, partial $\eta^2 = .01$, and a significant simple effect that low achievers with SDT-based support learned better than those without, $F(1, 60) = 26.40$, $p < .001$, partial $\eta^2 = .31$.

With regard to AIAX, the analyses revealed that there was a significant main effect of needs support from teachers, $F(1,122) = 3.89$, $p = .05$, partial $\eta^2 = .03$, a significant main effect of achievement, $F(1, 122) = 36.12$, $p < .001$, partial $\eta^2 = .23$, and a significant interaction effect, $F(1, 122) = 20.98$, $p < .001$, partial $\eta^2 = .15$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = 1.99$, $p = .16$, partial $\eta^2 = .03$, a significant simple effect in the control group that high achievers learned better than low achievers, $F(1, 60) = 36.26$, $p < .001$, partial $\eta^2 = .38$, no simple effect for high achievers, $F(1, 61) = 4.04$, $p = .05$, partial $\eta^2 = .06$, and a significant simple effect that low achievers with SDT-based support learned better than those without, $F(1, 60) = 17.71$, $p < .001$, partial $\eta^2 = .23$.

With regard to AIIM, the analyses revealed that there was a significant main effect of needs support from teachers, $F(1,122) = 16.99$, $p < .001$, partial $\eta^2 = .12$, a significant main effect of achievement, $F(1, 122) = 26.63$, $p < .001$, partial $\eta^2 = .18$, and a significant interaction effect, $F(1, 122) = 27.06$, $p < .001$, partial $\eta^2 = .18$. The results of follow-up analyses indicated no simple effect for the SDT-based group, $F(1, 61) = .13$, $p = .72$, partial $\eta^2 = .002$, a significant simple effect in the control group that high achievers learned better than low achievers, $F(1, 60) = 47.13$, $p < .001$, partial $\eta^2 = .44$, no simple effect for high achievers, $F(1, 61) = .89$, $p = .35$, partial $\eta^2 = .01$, and a significant simple effect that low achievers with SDT-based support learned better than those without, $F(1, 60) = 39.20$, $p < .001$, partial $\eta^2 = .40$.

To answer RQ2, with regard to perceived needs satisfaction, the analyses revealed that there was a significant main effect of support for autonomy, $F(1,123) = 56.58$, $p < .001$, partial $\eta^2 = .32$, competence, $F(1,123) = 78.22$, $p < .001$, partial $\eta^2 = .38$, and relatedness $F(1,123) = 38.18$, $p < .001$, partial $\eta^2 = .33$. A significant main effect was found for achievement in autonomy, $F(1,123) = 11.77$, $p = .001$, partial $\eta^2 = .09$, competence, $F(1,123) = 15.04$, $p < .001$, partial $\eta^2 = .11$, and relatedness, $F(1,123) = 59.93$, $p < .001$, partial $\eta^2 = .10$. No significant interaction effect was found in autonomy, $F(1,123) = 2.47$, $p = .12$, partial $\eta^2 = .02$, competence, $F(1,123) = 3.49$, $p = .06$, partial $\eta^2 = .03$, or relatedness, $F(1,123) = .09$, $p = .77$, partial $\eta^2 = .001$. The results of follow-up analyses showed that the SDT-based group perceived greater autonomy, competence, and relatedness than the control group, $F(1,126) = 51.04$, $p < .001$, $F(1,126) = 68.43$, $p < .001$, and $F(1, 126) = 54.62$, $p < .001$, respectively. The analyses also showed that high achievers perceived greater autonomy, competence, and relatedness than low achievers, $F(1,126) = 7.75$, $p = .006$, $F(1, 126) = 8.80$, $p = .004$, and $F(1,126) = 8.57$, $p = .004$, respectively.

To answer RQ3, the analyses revealed that the high and low achievers in the SDT-based group improved their AI readiness (high: $t(31) = 3.85$, $p = .001$; low: $t(31) = 8.00$, $p < .001$), confidence (high: $t(31) = 2.90$, $p = .007$; low: $t(31) = 7.38$, $p < .001$), attitude (high: $t(31) = 2.80$, $p = .009$; low: $t(31) = 6.56$, $p < .001$), and intrinsic motivation to learn AI (high: $t(31) = 4.46$, $p < .001$; low: $t(31) = 8.40$, $p < .001$). Low achievers, but not high achievers, also eased their AI anxiety (high: $t(31) = 1.68$, $p = .103$; low: $t(31) = 25.40$, $p < .001$),

To summarize the results of Study 2, see Table, 4, the SDT-based program did not create significant differences between high and low achievers on AI learning (RQ1), and performed significantly better in satisfying the three needs (RQ2). Regardless of their achievement level, the SDT-based program significantly enhanced students' perceived AI learning, with improvements in AIRD, AICF, AIAT, and AIIM (RQ3). Low achievers also felt less anxious about AI.

Discussion

This project aimed to create a high-quality AI program for K–12. The two studies examined whether an AI program designed with a needs satisfaction approach would enhance student AI learning, and whether it would have the same effects on (1) girls and boys and (2) high and low achieving students. The results have three major empirical implications and make two theoretical contributions. Three practical suggestions are also offered.

Empirical Implications

The first empirical implication is that the proposed needs support strategies satisfied the students' three SDT needs better than normal teaching approaches (see RQ2 in both studies). The strategies used in this project were adopted from the two SDT-based studies of Chiu (2021b, 2021c), in which their positive effects were confirmed in K–12 online and blended learning environments. The present findings support the effectiveness of these strategies for face-to-face classroom teaching. Therefore, the strategies used in the AI program appear to be effective in satisfying student needs in the three teaching scenarios of face-to-face, online, and blended learning.

The second implication is that the SDT-based program improved student perceived AI learning for both boys and girls, and both high and low achievers, with the only exception being the AI anxiety of high achievers (see RQ3 in both studies). These findings confirm that satisfying needs can better engage students in learning AI, which are consistent with most SDT-based studies (Chiu, 2021b, 2021c; Skinner et al., 2008; Vollet et al., 2017). According to SDT, when all three innate needs are met, students increasingly internalize their motivation until they are driven by something intrinsic to the activity (Ryan & Deci, 2020). Their motivational orientation can move through a continuum, from amotivation to extrinsic motivation to intrinsic motivation. Intrinsic motivation acts as a fuel that can better engage students in AI learning. Accordingly, when teachers can satisfy the needs for autonomy, competence, and relatedness in AI teaching, boys and girls, and high and low achievers with any motivation orientation are more likely to be engaged in learning.

The third implication is that the SDT-based program was of equal benefit to girls and boys and to high and low achieving students at fostering perceived AI learning, whereas the program adopting standard teaching approaches benefited (i) boys more than girls and (ii) high more than low achievers (see RQ1 in both studies). These results align with those of studies of learner expertise (e.g., Chiu & Mok, 2017; Chiu & Lim, 2020; Chiu et al., 2020; Leslie et al., 2012; Rey & Fischer, 2013). These studies suggested that aspects of learning environments, such as materials and teacher–student interactions, should be designed for students at different levels of expertise: that is, one design does not fit all. A plausible explanation for our finding, therefore, is that an instructional design that benefits highly motivated students may be detrimental for less motivated students (Kalyuga, 2007). Providing needs support allowed the students to design their preferred learning path, process, and outcomes. Supporting the need for competence provides less irrelevant information that does not fit their academic ability; supporting the need for relatedness makes problems more relevant and teacher–student interactions more welcoming; and supporting autonomy has positive effects on support for competence and relatedness because the three needs interact according to SDT (Chiu, 2021b, 2021c; Skinner et al., 2008; Vollet et al., 2017). Hence, SDT-based teaching encourages students to create an AI learning process that fits their needs and thus generates greater engagement in AI learning.

As an engineering topic, AI is typically perceived as a subject for boys and high achievers, which reduces the motivation of girls and students who are weaker in coding (Delaine et al., 2016; Ibe et al., 2018). Therefore, another plausible explanation is that the standard teaching approach (business as usual) did not challenge this perception. The female students and low achievers might have been demotivated before their AI learning began, might have felt incompetent in the subject, and might have regarded AI learning as irrelevant. Therefore, they failed to move through the continuum of motivation for greater engagement (Ryan & Deci, 2020). Moreover, this could be explained by the first implication: that the students in the SDT-based program perceived stronger autonomy, competence, and relatedness. Girls and low achievers had their needs supported in the SDT-based program, but not in the program delivered with a standard teaching approach. In the SDT-based program, the needs satisfaction levels of these underrepresented students were the same as those of the boys and high achievers. It appears that the SDT-based program enables all students to internalize their learning experience for high-quality motivation, and then find their learning joyful and relevant, gain a sense of competence, and own their own learning.

Theoretical Contributions

The first and second empirical implications described above contribute to SDT by presenting more evidence of how needs support from teachers relates to inclusive and diverse engineering education in the K–12 setting. Most related studies of K–12 education have used the three needs to explain the motivation and engagement of students of different genders, achievement levels, and cultures (Chiu & Mok, 2017; Chiu & Lim, 2020; Standage et al., 2005; Lietaert et al., 2015; Roorda et al., 2011). Furthermore, most studies have been conducted in non-engineering domains, such as physical education. For example, boys, Western students, and high achievers expect more autonomy support than girls; and girls, Eastern students, and low achievers prefer more relatedness support (Iyengar & Lepper, 1999; Ryan & Deci, 2020). The results of this project confirmed the effectiveness of its proposed student needs support from teacher strategies to promote inclusive and diverse education in the discipline of engineering, which features serious inequities. In other words, this project suggests that SDT can promote well-being in all students, regardless of their gender and achievement level, in engineering education.

Second, this project is built on the corresponding author's research into learner expertise (e.g., Chiu & Mok, 2017; Chiu & Lim, 2020; Chiu et al., 2020). Hence, the findings of this project theoretically contribute to research related to learner expertise and motivation, such as the Kalyuga expertise reversal effect (Kalyuga, 2007). These studies showed that one design does not fit all. For example, well-structured materials, emotional designs, and specific guidance should benefit low achievers but not high achievers. Most of these studies looked at diversity issues from the perspective of cognitive science (i.e., competence in SDT), such as multiple modalities, Mayer's multimedia learning (Mayer, 2009), and emotional multimedia designs. For example, an instructional design tailored for low achievers may be more helpful for high achievers to maximize cognitive capacity in less-structured environments. This project took the new and different angle of psychological needs to study this issue of learner expertise, with the findings suggesting the importance of supporting motivation in students by providing needs support for students with different expertise (represented by gender and achievement in this project). This suggests that to cater to learner expertise in building engagement, supporting the needs for autonomy and relatedness is just as important as supporting the need for competence, particularly in engineering education.

Practical Suggestions

This study offers AI (and general engineering) curriculum coordinators and teachers three practical suggestions for providing high-quality engineering education. The first practical suggestion is to provide teachers with professional development training on supporting student needs. Trained teachers will have a better understanding of their motivational behaviors (Chiu & Churchill, 2016; Chiu et al., 2021). Hence, to boost their students' energy, they are more likely to design classrooms and online learning environments that support student needs, to connect with their students, and to make AI learning more relevant. This energy will then serve as a source of engagement for students of AI (Chiu et al., 2021).

The second suggestion is for AI curriculum coordinators to design a flexible and relevant AI curriculum for K–12. This design will empower AI teachers to tailor a program to their own classrooms and students. Compared with higher education, K–12 students feature greater learning diversity within and across schools, and have less self-directed learning competencies (Chiu et al., 2021). For example, a school may need more than one AI program for different classes at the same grade level. Flexibly and relevance are very important for K–12 AI education because a rigid AI curriculum will discourage teachers from designing for students with different levels of expertise and experience.

The third suggestion is to design AI laboratories that support student needs. In these laboratories, a range of AI technologies should be provided for students to choose their own learning approach, effective videos should be available for each of the technologies to allow for self-learning when students have technical problems, and seats and tables should be arranged in such a way to foster informal conversations between students and between students and teachers. This style of physical learning environment, which is common in universities (e.g., learning common) but not common in K–12 schools, will further support student needs.

Conclusions and Future Research

AI teaching is new at the K–12 level. This project suggests that a focus on needs satisfaction could engage boys and girls, and high and low achievers in AI learning. As they become more engaged, they are likely to gain more confidence, feel that the content is more relevant, and become intrinsically motivated to pursue further AI learning. This is the type of experiences that teachers need to offer to their students through engineering learning activities.

Four limitations of this project are noted here. First, while the results appear to support the effects of needs satisfaction on student AI learning, more studies are needed to validate the findings. The results could be extended by additional studies of more support strategies and other engineering domains, such as computational thinking (Moore et al., 2014). Second, qualitative studies would be useful to further explore needs support strategies for engineering education. Third, this project did not consider how teachers design their own AI programs. Future research could investigate how teachers design their own programs and how to develop teachers' capacities to address inclusion and diversity in their curriculum designs (Chiu & Churchill, 2016). Fourth, the program analyzed in this project was conducted during the summer break in the period affected by the COVID-19 pandemic, and its full effects may therefore not be revealed in the results. Future studies could adopt a longitudinal research design and study programs offered as part of regular schooling.

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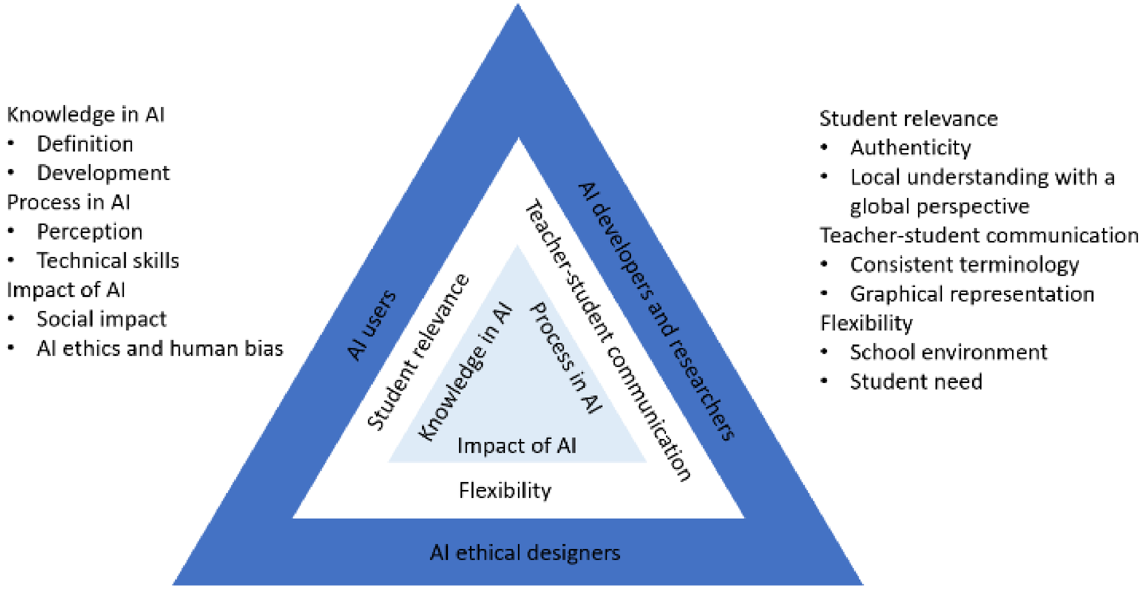

Figure 1. Curriculum Framework for K-12 AI, adapted from Chiu (2021a)

Table 1. Descriptive statistics for pre- and post-questionnaires in Study 1.

		Pre-questionnaire		Post-questionnaire	
Group	Variable	Mean	SD	Mean	SD
SDT-based and Boys (N = 32)	AI Readiness (AIRD)	3.51	.75	4.30	.72
	AI Confidence (AICF)	3.56	.78	4.45	.75
	AI Attitude (AIAT)	3.69	.81	4.51	.75
	AI Anxiety (AIAX)	2.30	.81	1.80	.82
	Intrinsic motivation to learn AI (AIIM)	3.57	.75	4.48	.75
	Perceived Autonomy	-	-	4.34	.47
	Perceived Competence	-	-	4.26	.52
	Perceived Relatedness	-	-	4.30	.54
SDT-based and Girls (N = 32)	AI Readiness (AIRD)	2.85	.88	3.78	.85
	AI Confidence (AICF)	2.83	1.11	3.73	.99
	AI Attitude (AIAT)	3.02	1.02	3.85	1.04
	AI Anxiety (AIAX)	3.01	.99	2.47	1.09
	Intrinsic motivation to learn AI (AIIM)	3.06	1.03	3.88	1.02
	Perceived Autonomy	-	-	4.05	.58
	Perceived Competence	-	-	4.14	.64
	Perceived Relatedness	-	-	4.02	.69
Control and Boys (N = 32)	AI Readiness (AIRD)	3.59	.77	4.17	.68
	AI Confidence (AICF)	3.77	.75	4.27	.72
	AI Attitude (AIAT)	3.77	.80	4.23	.71
	AI Anxiety (AIAX)	2.36	.97	1.76	.76
	Intrinsic motivation to learn AI (AIIM)	3.70	.73	4.30	.73
	Perceived Autonomy	-	-	3.40	.96
	Perceived Competence	-	-	3.38	.98
	Perceived Relatedness	-	-	3.40	1.11
Control and Girls (N = 32)	AI Readiness (AIRD)	2.85	.88	2.72	1.04
	AI Confidence (AICF)	2.83	1.11	2.80	1.15
	AI Attitude (AIAT)	3.02	1.02	2.93	1.20
	AI Anxiety (AIAX)	3.01	1.00	3.24	1.27
	Intrinsic motivation to learn AI (AIIM)	2.72	1.03	2.96	1.19
	Perceived Autonomy	-	-	2.90	.61
	Perceived Competence	-	-	2.88	.58
	Perceived Relatedness	-	-	2.98	.65

Table 2. Summary of the results of Study 1.

RQ1 (ANCOVA)			
Variable	Interaction effect	SDT-based	Control
AI Readiness (AIRD)	Significant	Insignificant[1]	Significant[2]
AI Confidence (AICF)	Significant	Insignificant[1]	Significant[2]
AI Attitude (AIAT)	Significant	Insignificant[1]	Significant[2]
AI Anxiety (AIAX)	Significant	Insignificant[1]	Significant[2]
Intrinsic motivation to learn AI (AIIM)	Significant	Insignificant[1]	Significant[2]
RQ2 (ANOVA)		Group	Gender
Perceived Autonomy	Insignificant	Significant[3]	Significant[4]
Perceived Competence	Insignificant	Significant[3]	Significant[4]
Perceived Relatedness	Insignificant	Significant[3]	Significant[4]
RQ3 (pair t-tests)	SDT-based (boys)	SDT-based (girls)	
AI Readiness (AIRD)	Significant[5]	Significant[6]	
AI Confidence (AICF)	Significant[5]	Significant[6]	
AI Attitude (AIAT)	Significant[5]	Significant[6]	
AI Anxiety (AIAX)	Significant[5]	Significant[6]	
Intrinsic motivation to learn AI (AIIM)	Significant[5]	Significant[6]	

Note: Insignificant[1] – no significant difference between boys and girls; Significant[2] – significant difference between boys and girls; Significant[3] – significant difference between the SDT-based and control groups; Significant[4] – significant difference between boys and girls; Significant[5] – significant difference between pre- and post- questionnaires for boys; Significant[6] – significant difference between pre- and post- questionnaires for girls.

Table 3. Descriptive statistics for pre- and post-questionnaires in Study 2.

		Pre-questionnaire		Post-questionnaire	
Group	Variable	Mean	SD	Mean	SD
SDT-based and low achievers (N = 32)	AI Readiness (AIRD)	2.45	.84	3.45	.72
	AI Confidence (AICF)	2.51	.95	3.45	.95
	AI Attitude (AIAT)	2.51	.73	3.47	.85
	AI Anxiety (AIAX)	3.56	.99	2.60	.92
	Intrinsic motivation to learn AI (AIIM)	2.81	.91	3.84	.87
	Perceived Autonomy	-	-	4.06	.85
	Perceived Competence	-	-	4.12	.66
	Perceived Relatedness	-	-	3.95	.70
SDT-based and high achievers (N = 32)	AI Readiness (AIRD)	3.72	.70	4.30	.67
	AI Confidence (AICF)	3.80	.75	4.33	.74
	AI Attitude (AIAT)	3.80	.78	4.30	.73
	AI Anxiety (AIAX)	2.18	.81	1.88	.64
	Intrinsic motivation to learn AI (AIIM)	3.60	.75	4.30	.68
	Perceived Autonomy	-	-	4.34	.74
	Perceived Competence	-	-	4.38	.59
	Perceived Relatedness	-	-	4.42	.62
Control and low achievers (N = 31)	AI Readiness (AIRD)	2.48	.84	2.55	.95
	AI Confidence (AICF)	2.46	.98	2.49	.85
	AI Attitude (AIAT)	2.46	.76	2.46	.88
	AI Anxiety (AIAX)	3.44	.99	3.47	.97
	Intrinsic motivation to learn AI (AIIM)	2.65	.97	2.68	.87
	Perceived Autonomy	-	-	2.73	.84
	Perceived Competence	-	-	2.70	.85
	Perceived Relatedness	-	-	2.81	.91
Control and high achievers (N = 32)	AI Readiness (AIRD)	3.65	.72	4.33	.64
	AI Confidence (AICF)	3.79	.74	4.42	.61
	AI Attitude (AIAT)	3.82	.78	4.39	.61
	AI Anxiety (AIAX)	2.38	.95	1.57	.65
	Intrinsic motivation to learn AI (AIIM)	3.70	.73	4.47	.60
	Perceived Autonomy	-	-	3.46	.88
	Perceived Competence	-	-	3.46	.85
	Perceived Relatedness	-	-	3.37	.92

Table 4. Summary of the results of Study 2.

RQ1 (ANCOVA)			
Variable	Interaction effect	SDT-based	Control
AI Readiness (AIRD)	Significant	Insignificant[1]	Significant[2]
AI Confidence (AICF)	Significant	Insignificant[1]	Significant[2]
AI Attitude (AIAT)	Significant	Insignificant[1]	Significant[2]
AI Anxiety (AIAX)	Significant	Insignificant[1]	Significant[2]
Intrinsic motivation to learn AI (AIIM)	Significant	Insignificant[1]	Significant[2]
RQ2 (ANOVA)		Group	Achievement
Perceived Autonomy	Insignificant	Significant[3]	Significant[4]
Perceived Competence	Insignificant	Significant[3]	Significant[4]
Perceived Relatedness	Insignificant	Significant[3]	Significant[4]
RQ3 (pair t-tests)	SDT-based (high achievers)	SDT-based (low achievers)	
AI Readiness (AIRD)	Significant[5]	Significant[6]	
AI Confidence (AICF)	Significant[5]	Significant[6]	
AI Attitude (AIAT)	Significant[5]	Significant[6]	
AI Anxiety (AIAX)	Significant[5]	Significant[6]	
Intrinsic motivation to learn AI (AIIM)	Significant[5]	Significant[6]	

Note: Insignificant[1] – no significant difference between high and low achievers; Significant[2] – significant difference between high and low achievers; Significant[3] – significant difference between the SDT-based and control groups; Significant[4] – significant difference between high and low achievers; Significant[5] – significant difference between pre- and post- questionnaires for high achievers; Significant[6] – significant difference between pre- and post- questionnaires for low achievers.