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Perceptions of and Behavioral Intentions towards Learning Artificial Intelligence in Primary School Students

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ABSTRACT: Artificial Intelligence (AI) is increasingly popular, and educators are paying increasing attention to it. For students, learning AI helps them better cope with emerging societal, technological, and environmental challenges. This theory of planned behavior (TPB)-based study developed a survey questionnaire to measure behavioral intention to learn AI (n = 682) among primary school students. The questionnaire was administered online, and it measured responses to five TPB factors. The five factors were (1) self-efficacy in learning AI, (2) AI readiness, (3) perceptions of the use of AI for social good, (4) AI literacy, and (5) behavioral intention. Exploratory factor analysis and a subsequent confirmatory factor analysis were used to validate this five-factor survey. Both analyses indicated satisfactory construct validity. A structural equation model (SEM) was constructed to elucidate the factors' influence on intention to learn AI. According to the SEM, all factors could predict intention to learn AI, whether directly or indirectly. This study provides new insights for researchers and instructors who are promoting AI education in schools.

Keywords: Artificial intelligence, Self-efficacy, Readiness, Social good, Literacy, Behavioral intention

1. Introduction

Artificial intelligence (AI) is rapidly developing, and it has become an integral part of our everyday lives. AI, which is ubiquitously adopted in many computing devices, is changing how we search for information, communicate with others, and make everyday arrangements (Lin et al., 2021). As an emerging field (regarded as part of the fourth industrial revolution), AI has also impacted the domain of education, potentially engendering a fourth education revolution (Roll & Wylie, 2016; Seldon & Abidoye, 2018). AI has been used in education for a range of purposes—including in administrative support systems (Sellar & Gulson, in press); intelligent tutoring systems (Ma, Adesope, Nesbit, & Liu, 2014; VanLehn, 2011); adaptive learning systems (Nakic, Granic, & Glavinic, 2015); and social assistive robots, used to make learning more engaging for preschool children (Fridin, 2014). The range of AI applications will only continue to grow, and the technology is likely to inspire new educational practices (So et al., 2020). However, as noted by Zawacki-Richter, Marín, Bond, and Gouverneur (2019) in their comprehensive review, studies on AI in education have focused only on higher education and on AI system development; research on how AI is taught and learned is therefore required.

Current K-12 students will face an AI-powered future, which is likely to demand greater creativity, critical thinking, and aptitude with technology (Aoun, 2017; Hwang & Fu, 2020); these can be enhanced through learning about AI. However, very little research has been conducted on learning AI among K-12 students (Zawacki-Richter et al., 2019). Most previous studies on AI in a K-12 context have been focused on the pedagogical use of AI systems—in, for example, intelligent tutoring systems—rather than the learning of AI itself. Although these systems have had demonstrable effectiveness (Ma et al., 2014), the role of the computer has evolved from that of being the tutor to that of a tutee or teachable agent (Chin, Dohmen, & Schwartz, 2013; Matsuda, Weng, & Wall, 2020). Regardless of the pedagogical model employed, students have used AI to learn something else; students have rarely learned about AI itself. Meanwhile, the need to develop AI curricula for younger students to acquire AI knowledge has begun to emerge (Knox, 2020). In China, for example, K-12 AI textbooks have been published, and curricular frameworks on AI have been formulated (Knox, 2020; Qin, Ma, & Guo, 2019; Tang & Chen, 2018); pilot testing of the AI curricula is ongoing. In general, the AI curricula in China covers the following: everyday applications of AI, how AI can solve problems (such as the early diagnosis of diseases), the core concepts underlying AI (e.g., data representation, machine learning, visual recognition, and the algorithm), and how to write code (Qin et al., 2019; Tang & Chen, 2018).

Against this background, this study investigated how primary school students learn AI, focusing specifically on their intention towards learning AI. This study adopted the theory of planned behavior (TPB) and developed a survey questionnaire. The AI curriculum had the dual aims of preparing students for an AI-powered workplace and to encourage students to consider AI as a possible future career (Qin et al., 2019). The first aim was advanced by promoting basic AI literacy. In general, greater AI literacy makes students more willing and able to engage with new technologies (Corbeil & Valdes-Corbeil, 2007; Parasuraman & Colby, 2015) and less fearful of an AI-powered world (Wang & Wang, 2019). The second aim was advanced by motivating students to continue learning AI. In general, such behavioral intention is partially formed by behavioral beliefs regarding first, the consequences of an action and second, one's ability to perform the action (Ajzen, 2012). Furthermore, students are more willing to learn AI if their ability to learn AI is fostered and if they understand the benefits of learning AI (Keller, 2010; Fishbein & Ajzen, 2010). This implies that designers of an AI curriculum must ensure (1) an appropriate level of difficulty and (2) ample illustrations with meaningful examples. In particular, meaningful illustrative examples can motivate students through illustrating AI's contributions to society. In general, such purposeful learning empowers students and encourages student participation (Yeager & Bundick, 2009). Computer skills curricula have had an aim of helping students understand computing's contributions to for social good (Goldweber et al., 2011). However, empirical studies between computing for social good and students' intention to learn computing seems lacking. Social good may be associated with behavioral intention to learn AI. Thus, the goal of this study is to include social good as purpose of AI learning to propose a framework guided by TPB to investigate the influential factors affecting behavioral intention towards learning AI. To achieve the goal, we develop and validate a contextualized survey.

2. Literature review

2.1. Behavioral intention to learn AI

The TPB (Ajzen, 1985) was developed from the theory of reasoned action (Fishbein & Azjen, 1975). Fishbein and Azjen (2010) conceptualized human behavior as reasoned action that follows from behavioral intention (BI); BI was, in turn, conceptualized as being based on "the information or beliefs people possess about the behavior under consideration" (p. 20). Such information is typically acquired through mass media or formal education. However, the same piece of information may be interpreted differently by different people depending on their individual-level traits, such as their personality and demographic characteristics. These differences mark those beliefs that determine BI. Fishbein and Azjen noted three types of individual-level beliefs: attitude towards behaviors (ATB), subjective norms (SN), and perceived behavioral control (PBC). These factors have consistently accounted for the many variances in learners' behavioral intentions in many empirical studies (Ajzen, 2012). Findings in the literature have jointly indicated that an individual is more likely to perform behaviors that are perceived to (1) yield positive outcomes, (2) be normatively desirable, and (3) involve controllable behavioral processes and outcomes. The TPB has been applied in numerous contexts, such as in technology adoption (Cheon, Lee, Crooks, & Song, 2012), health care (Chau & Hu, 2002), and e-commerce and business (Liao, Chen, & Yen, 2007). These studies have allowed social scientists to understand the influences on people's intention to use technology.

In the field of education, the TPB has been adopted by studies examining the intention to use technology, both in students and teachers (Cheon et al., 2012; Mei, Brown, & Teo, 2018). For example, Cheng, Chu, and Ma (2016) investigated students' attitude towards e-collaboration, and they noted that SN and PBC significantly predicted their intention to engage in e-collaboration. With regard to AI education, however, TPB-based research has yet to be conducted despite the increasing popularity of K-12 AI education. Thus, this study used the TPB to investigate the psychological factors that influence primary students' perceptions of and intentions towards learning AI. The findings help educators create favorable conditions for learning AI in the primary school classroom.

2.2. Background factors

As noted by Fishbein and Ajzen (2010), BI is shaped by background factors, which are categorized into individual (e.g., personality), societal (e.g., education, age and gender), and epistemic (e.g., knowledge and ways of thinking) factors. An individual is technologically literate if they know how technology works and how to use technology to solve problems (Moore, 2011)—including using technology to acquire, interpret, and apply knowledge (Davies, 2011). Thus, this study defines a student as AI literate if they know what constitutes AI and know how to apply AI to different problems. According to the TPB (Fishbein & Ajzen, 2010), AI literacy is foundational to the behavioral, normative, and control beliefs that would consequently predict the BI (i.e., see Table 4, H1–H4). Previous studies have demonstrated that perceived technology literacy predicts (1) effort expectancy in e-learning (Mohammadyari & Singh, 2015) and (2) teachers' and students' intention to engage in mobile learning (Jong et al., 2018; Mac Callum, Jeffrey, & Kinshuk, 2014). Mei et al. (2018) also demonstrated that perceived technological literacy positively predicts learning intention, specifically in preservice teachers' intention to use technology in language education. In addition, Rubio, Romero-Zaliza, Mañoso, and de Madrid (2015) reported gender differences in the BI of university students towards coding after an introductory programming course. Their study also noted that this gender difference was eliminated by including the physical computing approach in course design. In general, their study elucidated the factors influencing BI and how TPB can be used to improve BI in students and teachers of technology-based courses.

2.3. Attitudes and behavioral intention

BI is influenced by an individual's ATB. ATB is defined as an individual's favorable or unfavorable feelings towards a psychological object (Fishbein & Ajzen, 2010). Ajzen (2012) stated that the favorableness associated with a behavior is largely based on the evaluative beliefs formed regarding the behavior's consequences. As mentioned, education aims to foster (1) citizens who contribute to social good and (2) members of the workforce who are well-equipped for the future workplace (Duncan & Sankey, 2019; Lo, 2010; White, 2010). Such aims have been incorporated into the present-day AI curriculum in China (Qin et al., 2019; Tang & Chen, 2018). In the context of computer science education, few empirical studies have investigated the influence on intention to learn AI from perceptions of AI's contributions to society; this is despite the fact that computing for social good is a recognized curriculum emphasis (Goldweber et al., 2011) and the strong ethical concern among AI scholars regarding the use of AI for social good (Bryson & Winfield, 2017; Floridi et al., 2018). Drawing from general educational research on occupational aspiration in adolescents, Yeager and Bundick (2009) observed a greater willingness to learn when their participants had goals that were directed towards something greater than themselves (Chang et al., 2020; Huang et al., 2019; Jong, Lee, & Shang, 2013; Lan et al., 2018). The idea of learning to use knowledge to serve others aligns with the philosophy of the Confucius which posits education as a means to perfect one's self in service of others (Basharat, Iqbal, & Bibi, 2011). By contrast, learning disengagement is likely if one learns merely to perform well in standardized tests (Dong et al., 2020; Jong et al., 2008; Taylor et al., 2013). Thus, the motivation to learn AI for social good can be considered as an attitude towards learning (Webb, Green, & Brashear, 2000). Webb et al. (2000) developed a scale for measuring an individual's attitude towards helping others, which is similar to our scale; such an attitude is strongly associated with the intention and willingness to act (Briggs, Peterson, & Gregory, 2010). According to the preceding analysis, this study posits that curriculum designed to promote learning for social good could strengthen students' intention to learn. Whether or not an AI curriculum that illustrates AI for social good will shape students' favorable ATB such that they could predict students' intention to learn AI remains to be investigated (i.e., H9 in Table 4).

The instrumental value of any curriculum is also to get students ready for the future. Among students with a favorable ATB, whether a given pedagogical technique prepares them well for the future requires empirical verification. The technology readiness index (TRI) was proposed by Parasuraman (2000) to measure one's propensity to use technology for a given set of goals. In the TRI, greater readiness indicates greater perceived control over a given piece of technology and a greater likelihood to use it often. The sense of readiness was deduced by the users from the knowledge and the confidence they possess (i.e., H3 and H6 in Table 4). Technology readiness has been used to explain the adoption of new technology (Parasuraman & Colby, 2015) and use of technology (Godoe & Johansen, 2012). Considering these findings in the literature, this study hypothesized that greater technological readiness predicts greater intention to learn AI. Specifically, the present study adapted items from Parasuraman's (2000) TRI to measure AI readiness in primary school students.

The sense of being ready should be considered as a self-oriented positive attitude, and one's positive attitude towards technology use can explain one's intention to use it (Chiu, 2017; Teo & Tan, 2012). Thus, using AI for social good may contribute to the participants' readiness to use it (i.e., H8 in Table 4). For example, Bertot, Jaeger, and Grimes (2010) illustrate how technology could promote transparency (a form of social good) that shape government adoption towards e-service. The TRI has been studied with the TPB in the context of e-commerce (Grandon, & Ramirez-Correa, 2018), where the TRI was employed as a background factor explaining how innovativeness changes the significance of PBC in predicting intention to adopt e-commerce. Furthermore, Chen and Li (2010) noted that intention to use e-services is predicted by ATB, SN, and PBC, which are, in turn, predicted by a combined factor of TRI. In both of the aforementioned studies, the TRI has been treated as a background personality trait that positively influences the intention to use technology. However, both studies had adult participants, for whom the TRI could be considered a background factor. However, among young learners and especially for an emerging discipline like AI, technology readiness is more likely to be an outcome of learning, and such technological readiness, in turn, contributes to intention to learn (H10 in Table 4).

2.4. Perceived behavioral control and behavioral intention

PBC refers to one's perceived capability of performing a behavior (Ajzen, 1991). According to Ajzen (2002), PBC is conceptually similar to Bandura's concept of self-efficacy, defined as the perceived ease or difficulty in performing a behavior. The feeling of certainty and confidence in successfully executing a behavior under examination constitutes the core items that are frequently used to indicate measure self-efficacy (Fishbein & Ajzen, 2010). However, Ajzen (2002) also noted that beliefs regarding self-efficacy and beliefs regarding the controllability of a behavior can be two distinctive factors of PBC (see also Rhodes & Courneya, 2004). Nonetheless, Ajzen's (2002) analysis on this issue has pointed out that the self-efficacy factor is a stronger predictor for intention. Furthermore, studies commonly measure self-efficacy or confidence but not both (Zhang, Wei, Sun, & Tung, 2019).

Studies have demonstrated that in students, confidence in learning predicts continuous learning (Lee, 2010) and the intention to use technology as a learning tool (Garland & Noyes, 2005). In many TPB studies, self-efficacy is a commonly adopted PBC scale, and participants with self-efficacy have been noted to have greater BI (Rhodes & Courneya, 2004) (H7 in Table 4).

TPB-based studies have rarely investigated the relationship between PBC factors (e.g., self-efficacy) and ATB. Nonetheless, Yildiz's (2018) study shows that students' technology and communication self-efficacy contributes to their flipped learning readiness, which in turn predict their attitudes toward programming. It provides some support that in students, self-efficacy in learning AI predicts sense of readiness and predicts attitudes towards learning AI for social good and their sense of readiness (i.e., H5 & H6 in Table 4).

In sum, we hypothesized that for primary school students, the TPB could explain intention to learn AI. A structural model of students' BI and the variables that influence their intention to learn AI was developed (see Table 4 and Figure 1). Our research questions were as follows: (1) Is the 5-factor survey for primary school students' perception of AI learning valid and reliable? (2) Are the hypothesized relationships (H1-H 10) among the factors supported?

3. Method

3.1. Participants

Convenience sampling was used to enroll participants (N = 682, 52.05% male) in Beijing, China. The students were in the third to the sixth grades, with an average age of 9.87 years (SD = 0.97 years). The school arranged for the participants to be enrolled in an AI course covering basic AI knowledge. Specifically, the course covered the history of AI, applications of AI (e.g., in image and voice recognition, content recommendation, and machine learning), and the ethical use of AI. As noted in classroom observations, the participants learned about basic AI concepts and data representations; they also participated in the hands-on use of AI products and discussions on the use of AI products. Students spent an average of 6.04 h (SD = 2.56 h) on AI-related learning activities. The students were invited by their teachers to voluntarily respond to an online survey in the classroom at the end of the semester. The students took approximately 15 minutes to complete the survey. They were instructed to respond to each item by choosing the option that best described their level of agreement.

3.2. Instruments

This study's survey was based on five constructs, some of which were adapted from previous studies and others comprised self-constructed items. Answers were scored on a 4-point Likert scale from 1 (*strongly disagree*) to 4 (*strongly agree*). The first part of the survey collected background data (grade, gender, age, and hours spent on AI learning). The second part of the survey measured student confidence in AI, AI readiness, perceptions of using AI for social good, AI literacy, and BI to engage in AI learning. The finalized items are presented in Table 1. The following is a brief description of the five constructs of the survey.

Self-efficacy in learning AI was adapted from Song and Keller's (1999) confidence scale (α = 0.70), which was initially designed to measure students' confidence in the context of computer-mediated instruction. The items measured students' "self-efficacy varying in their degree of difficulty" (Fishbein & Ajzen, 2010, p.158). Specifically, the items measured students' confidence in their understanding, in how far they will succeed should they put in effort, and in their understanding of both advanced material and the basic concepts. In this study, greater confidence indicated greater self-efficacy (Fishbein & Ajzen, 2010) in meeting the learning objectives of the AI class.

AI readiness was developed from the optimism subscale of the TRI (Parasuraman, 2000). AI readiness is the student's perceived level of comfort with the use of AI technology in their everyday lives. Students with greater AI readiness favor the adoption of AI technology. The original scale had 10 items, among which six items were adapted for use in the present study (for the 10 items, α = 0.78).

AI for social good comprised five self-constructed items. It measured students' beliefs regarding the use of AI knowledge to solve problems and improve people's lives. The items indicated students' awareness of one purpose of learning AI.

AI literacy comprised five items. The items were developed based on the primary school's AI curriculum. AI literacy measured students' perception of their understanding of AI and of their general ability to use AI in their everyday lives.

Behavioral intention comprised adaptations of three of the four items in Park, Nam, and Cha (2012). Their study investigated university students' BI to be engaged in mobile learning (for the four items, α = 0.91). Furthermore, one more item was used in this scale. That item was adapted from Liaw, Huang, and Chen (2007), who investigated the BI to use e-learning.

The survey was reviewed by five professors in the fields of computer engineering and educational technology. The survey was then revised based on their comments. Subsequently, two teachers from the participating schools modified the wording of the survey's questions to ensure that students were able to understand the items.

3.3. Data analysis

This study's data analysis proceeded in three phases. In the first phase, the participants were randomly assigned to two subsamples. One subsample comprised approximately one-third of the participants (n = 217, 55.76% male); it was used for exploratory factor analysis (EFA). The other subsample comprised the remaining participants (n = 465, 50.32% male); it was used for confirmatory factor analysis (CFA) and SEM.

Prior to the analyses, univariate and multivariate normality tests were conducted for the entire data set. With respect to univariate normality, we noted that no measured item had a skewness (range: −0.989 to −2.148) and kurtosis (range: 0.336 to 5.149) that were greater than the requisite maximum values of |3| and |8|, respectively (Kline, 2011). With respect to multivariate normality, Mardia's coefficient is the standard indicator. This value should be less than (k [k + 2]), where k is the number of observed variables (Raykov & Marcoulides, 2008). For this study, the coefficient value was 521.392, which was less than the requisite maximum of 22 × 24 = 528. Multivariate normality was thus satisfied.

EFA was conducted using SPSS (version 25) to clarify the structure of the subscales. Principal axis factoring analysis and the direct oblimin rotation method were applied to extract the factors. Items with cross loadings or factor loadings of < 0.5 were omitted. Alpha reliabilities were computed for all factors and items. Pearson correlation analysis was used to analyze the relationship between the factors. Subsequently, CFA was conducted to verify the construct validity of the instrument. Structural equation modeling (SEM) was then used for hypothesis testing in Amos for Structural Equation Modeling (version 23).

4. Results

4.1. Exploratory factor analysis of the measurement model

Table 1 summarizes the EFA results, including the mean, standardized deviation, factor loadings, and alpha reliabilities. The EFA extracted 22 items with factor loadings greater than 0.5 in the final version of the 5-factor measurement model. The Kaiser–Meyer–Olkin value was 0.910, and the value for Bartlett's test of sphericity was 4008.041 (df = 231, $p < .001$). These results indicated that the five factors had good explanatory power with respect to perception of AI learning.

The five factors explained 69.97% of the variance in perception of AI learning; they were self-efficacy in learning AI (four items, α = 0.88), AI readiness (five items, α = 0.88), perceptions of the use of AI for social good (five items, α = 0.92), AI literacy (four items, α = 0.91), and BI (four items, α = 0.90). The overall α value was 0.95, which suggested that these factors had satisfactory reliability and they were suitable for measuring perceptions of AI learning.

Table 1. Exploratory factor analysis results for intention to learn AI ($n = 217$)

Item	Factor loading
Self-efficacy, α = 0.88, M = 3.53, SD = 0.61	
C3 I am certain I can understand the most difficult material presented in the AI class.	0.77
C1 I feel confident that I will do well in the AI class.	0.76
C4 I am confident I can learn the basic concepts taught in the AI class.	0.73
C2 I believe that I can succeed if I try hard enough in the AI class.	0.58
Readiness, α = 0.88, M = 3.62, SD = 0.49	
RE2 It is much more convenient to use the products and services that use the latest AI technologies.	0.81
RE6 I feel confident that AI technologies will follow the instructions I give.	0.71
RE1 AI technology gives people more control over their daily lives.	0.69
RE3 I prefer to use the most advanced AI technology available.	0.66
RE4 I like AI technology that allows me to tailor things to fit my own needs.	0.66
Social good, α = 0.92, M = 3.63, SD = 0.54	
SG1 I wish to use my AI knowledge to serve others.	0.84
SG2 AI can be used to help disadvantaged people.	0.83
SG4 AI combined with design thinking can enhance my ability to help others.	0.70
SG3 AI can promote human well-being.	0.67
SG5 The use of AI should aim to achieve common good.	0.62
Literacy, α = 0.91, M = 3.59, SD = 0.58	
L2 I can use AI-assisted voice recognition software to search for information.	0.84
L1 I know that AI can be used to recognize images.	0.78
L4 I am able to use online AI translation tools.	0.74
L3 I can interact with AI assistants via speech recognition (e.g., Siri, DuerOS).	0.68
Behavioral intention, α = 0.90, M = 3.51, SD = 0.67	
BI3 I will continue to acquire AI-related information.	0.94
BI2 I will keep myself updated with the latest AI applications.	0.89
BI4 I intend to use AI to assist with my learning.	0.62
BI1 I will continue to learn AI.	0.52

4.2. Correlations among the factors

Pearson correlation coefficients were calculated to investigate the relationships among the five factors. As noted in Table 2, these factors were significantly and positively correlated (from $r = 0.54$ to $r = 0.63$).

Table 2. Correlations in the measured model ($n = 217$)

	1	2	3	4	5
1. Self-efficacy	(0.71)	0.62^{***}	0.54^{***}	0.58^{***}	0.60^{***}
2. Readiness		(0.71)	0.59^{***}	0.49^{***}	0.58^{***}
3. Social good			(0.73)	0.63^{***}	0.63^{***}
4. Literacy				(0.76)	0.55^{***}
5. Behavioral intention					(0.76)

Note. $^{***}p < .001$. Items on the diagonal are the square roots of the average variance extracted; off-diagonal elements are the correlation estimates.

4.3. Confirmatory factor analysis of the measurement model

The CFA further confirmed the construct validity and the structure of the measurement model. As detailed in Table 3, all item parameters were statistically significant.

The model had good fit: χ^2/df = 2.89 (< 5.0), RMSEA = 0.064 (< 0.08), SRMR = 0.044 (< 0.05), GFI = 0.90 (> 0.90), TLI = 0.94 (> 0.90), and CFI = 0.95 (> 0.90) (Hair, Black, Babin, Anderson, & Tatham, 2010). More generally, these results indicated that the survey items had good construct validity.

Moreover, the examination of the composite reliability (CR) of each sub-scale was greater than 0.70, and the average variance extracted (AVE) met or exceeded the value of 0.50: Self-efficacy in learning AI (CR = 0.80, AVE = 0.50), AI readiness (CR = 0.83, AVE = 0.50), AI for social good (CR = 0.85, AVE = 0.54), AI literacy (CR = 0.85, AVE = 0.58), and behavioral intention (CR = 0.84, AVE = 0.58), indicating satisfactory reliability and convergent validity of each sub-scale (see Hair et al., 2010). Discriminant indexes (See Table 2) were computed based on the AVEs.

Table 3. Confirmatory factor analysis results for intention to learn AI (n = 465)

Scale	Item	Mean	*SD*	Unstandardized estimate	Standardized estimate	*t*-value
Self-efficacy	C1	3.35	0.79	1	0.81	-
	C2	3.51	0.67	0.85	0.82	19.85^{***}
	C3	3.23	0.85	1.01	0.76	18.01^{***}
	C4	3.47	0.73	1.00	0.88	21.81^{***}
Readiness	RE1	3.60	0.64	0.99	0.84	19.28^{***}
	RE2	3.62	0.61	0.96	0.86	19.81^{***}
	RE3	3.53	0.70	1	0.77	-
	RE4	3.47	0.74	1.09	0.80	18.13^{***}
	RE6	3.36	0.81	0.97	0.64	14.17^{***}
Social good	SG1	3.54	0.70	1	0.89	-
	SG2	3.56	0.68	0.92	0.83	23.99^{***}
	SG3	3.58	0.66	0.87	0.82	23.60^{***}
	SG4	3.52	0.70	0.95	0.84	24.42^{***}
	SG5	3.58	0.69	0.88	0.80	22.24^{***}
Literacy	L1	3.58	0.66	1	0.86	-
	L2	3.60	0.62	0.96	0.87	22.75^{***}
	L3	3.55	0.68	0.93	0.77	19.19^{***}
	L4	3.64	0.65	0.88	0.76	18.86^{***}
Behavioral intention	BI1	3.44	0.76	0.94	0.86	25.94^{***}
	BI2	3.42	0.76	1	0.91	-
	BI3	3.40	0.76	0.95	0.86	26.25^{***}
	BI4	3.39	0.81	0.71	0.60	14.65^{***}

Note. $^{***}p < 0.001$.

4.4. SEM for hypotheses testing

SEM was used for hypothesis testing. The SEM model had good fit: χ^2/df = 2.91 (< 5.0), RMSEA = 0.064 (< 0.08), SRMR = 0.044 (< 0.05), GFI = 0.90 (> 0.90), TLI = 0.94 (> 0.90), CFI = 0.95 (> 0.90) (Hair et al., 2010). As shown in Table 4, eight out of ten hypotheses were confirmed, indicated that AI literacy significantly predicts Self-efficacy in learning AI and social good. Self-efficacy is a significant predictor for social good, AI readiness, and behavioral intention. Social good significantly predicts AI readiness and behavioral intention. AI readiness significantly predicts behavioral intention. The estimated standardized path coefficients are presented in Figure 1. The findings show that most hypothesized relationships among the sub-scales were supported.

Table 4. Hypotheses testing results from SEM

Hypothesis	Path	Unstandardized estimate	Standardized estimate	*t*-value	Hypotheses supported?
H1	Literacy —> Self-efficacy	0.68	0.59	11.67^{***}	Yes
H2	Literacy —> Social good	0.43	0.39	7.71^{***}	Yes
H3	Literacy —> Readiness	0.05	0.05	1.12	No
H4	Literacy —> Behavioral intention	-0.08	-0.06	-1.34	No

H5	Self-efficacy—> Social good	0.42	0.43	8.30***	Yes
H6	Self-efficacy —> Readiness	0.30	0.36	6.85***	Yes
H7	Self-efficacy —> Behavioral intention	0.40	0.37	6.52***	Yes
H8	Social good —> Readiness	0.45	0.52	9.23***	Yes
H9	Social good —> Behavioral intention	0.37	0.34	5.20***	Yes
H10	Readiness —> Behavioral intention	0.32	0.25	3.55***	Yes

Note. $^{***}p < 0.001$.

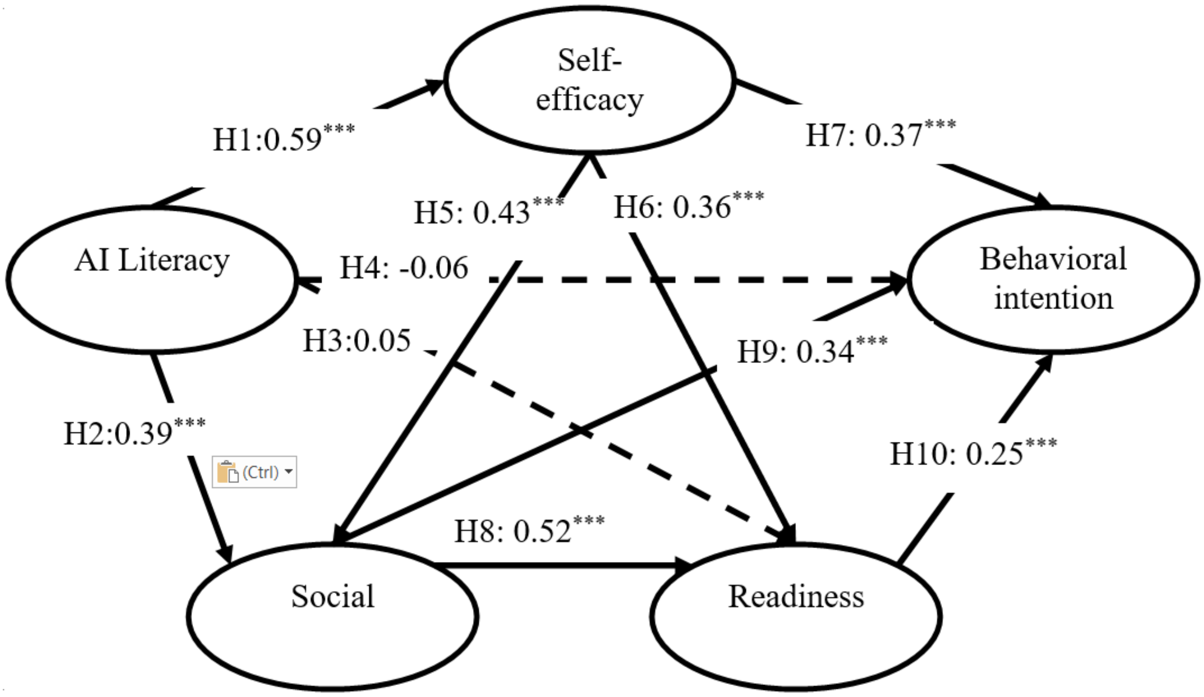

Figure 1. Structural model of the measured factors. *Note.* $^{***}p < 0.001$

5. Discussion and conclusions

Although AI has received much recent attention in the higher-education context, it has rarely been explored in the K-12 context (Zawacki-Richter et al., 2019). Considering the need to prepare young students for an AI-powered workplace, students' intention to learn AI must be investigated. This TPB-based study surveyed primary school students' intention to learn AI (Fishbein & Ajzen, 2010). Fishbein and Ajzen recognized the context dependence in people's assignment of weights to the factors pertaining to attitude, norms, and perceived control. Considering the context of the new AI curriculum, this study chose students' perceived AI literacy as a background factor; perceived use of AI for social good and readiness for the AI-powered world as their ATB; and confidence in learning AI as their PBC. These factors were hypothesized to predict students' intention to learn AI. The findings from 682 primary school students (Grades 3 to 6) in Beijing indicated that intention to learn AI was influenced by self-efficacy in learning AI, AI readiness, and perceived use of AI for social good. The background factor, AI literacy, only influenced students' self-efficacy in AI and perceptions of the use of AI for social good directly. The findings of this study are generally congruent with those of studies using the TPB, as formulated by Fishbein and Ajzen. Similar to the many previous TPB-based studies (Mei et al., 2018; Mohammadyari & Singh, 2015; Zhang et al., 2019), this study noted the TPB to be a useful theoretical framework for identifying factors that contribute to BI. Our findings suggest that to foster strong BI towards learning AI, developers of AI curricula should pay attention to students' ATB and PBC. The implications of this study are discussed as follows.

First, this study employed EFA and CFA to establish a valid and reliable five-factor survey that measures students' perception of learning AI. This survey can be used in future research on how curriculum design influences BI. Within the Web of Science Core Collection database, we identified 5470 studies containing the search term "theory of planned behavior." However, further separate searches within this result using "elementary OR primary" did not return with any study. This study therefore could further enrich the applicability of TPB in primary school contexts. For primary school students, their first experience of learning AI in formal educational ought to prepare them for the future AI-powered workplace. This study's survey indicated that the curriculum used by the participants could provide positive experiences and foster students' readiness and BI for learning AI in the future. Specifically, the mean scores for all measured factors were >3.5; a score of 3 constituted the neutral point in the 4-point scale that these factors were scored on. Our findings also elucidated the factors that influence BI.

The background factor of AI literacy was defined as the knowledge of AI that students acquired from the curriculum. In accordance with Fishbein and Ajzen's (2010) model that depicts knowledge or information as predicting ATB and PBC, and current studies applied to technology-based teaching and learning (Mei et al., 2018; Mohammadyari & Singh, 2015; Mac Callum et al., 2014); AI literacy is a significant predictor of the students' self-efficacy and the social good. However, it did not predict students' readiness and BI directly. This indicates that AI literacy is not a sufficient condition for being ready to learn or use AI. Gaining PBC (i.e., self-efficacy) and a belief that AI contributes to social good are necessary. Designers of AI curricula must, therefore, pay special attention to these aspects.

Self-efficacy was the most important factor that directly predicted students' BI, AI readiness, and perceptions about the use of AI for social good. While self-efficacy can predict students' BI in learning as indicated by past research (Lee, 2010; Garland & Noyes, 2005), the finding also points to the importance of PBC, and it contributes to the further understanding of the relationships between PBC and ATB in the context of learning AI. Little research has explicated the PBC may predict ATB and the implication of this study could be informative for future research involving curriculum design for an emerging field of study. In such a context, addressing students' self-efficacy could be crucial in shaping their evaluative beliefs about learning the subject matter.

Furthermore, perceptions of learning AI for social good significantly predicted students' readiness to learn AI and intention to learn AI. This suggests that AI curricula should allow students to solve real-world problems to illustrate how AI can be used to benefit others; this encourages students to delve deeper into AI. Such an emphasis on the use of AI for social good is congruent with current trends in computer science education (Goldweber et al., 2011; Bryson & Winfield, 2017; Floridi et al., 2018). Students are likely to regard the promotion of social good as a positive outcome of learning AI, which, in turn, fosters BI (Fishbein & Ajzen, 2010) and purpose in learning (Yeager & Bundick, 2009). Pedagogically, teachers should use examples and hands-on applications to illustrate how AI can be used for social good, thereby stimulating students' intention to learn AI. These strategies are reflected in the present-day AI curriculum in China (Qin et al., 2019).

Student readiness also predicts intention to learn. Greater readiness, as measured in this study, reflected a more positive perception of how useful AI is. Greater readiness was interpreted as another positive consequence of learning AI. AI literacy predicted readiness, not directly but only indirectly, through self-efficacy and the perception of using AI for social good; this finding is congruent with a previous finding that readiness grants an individual a sense of control by helping them use technology flexibly and efficiently (Parasuraman & Colby, 2015). This implies that readiness is not immediately obvious to students. However, if students are confident that they can learn and use AI for social good, they feel more ready to use AI. Furthermore, students who perceive AI to be useful have a greater intention to learn it; this finding is congruent with those of earlier studies (Mei et al., 2018; Yildiz, 2018).

In conclusion, the emergence of AI has greatly changed society and technology, and education must reform itself accordingly (Aoun, 2017; Seldon & Abidoye, 2018). Students ought to be prepared to learn AI early in their education. According to Fishbein and Ajzen (2010), people tend to deliberate on their actions when encountering a novel situation, of which the emergence of AI is one; the result of such deliberation, in turn, forms the cognitive foundation for future decisions. We recommend for educators to foster self-efficacy and emphasize the potential use of AI for social good. In doing so, students are more likely to have greater intention to learn AI, and they can thus be better prepared for an AI-powered future.

6. Limitations

This study has several limitations. First, this study was limited to the primary school students in Beijing, China. Further research should examine and compare K-12 students' AI learning from other cities or countries and levels of students. Second, this study considered only positive attitudes in its measures of intention to learn AI. However, adverse psychological factors, such as anxiety towards AI (Wang & Wang, 2019), should also be considered—especially considering the increasing adoption of AI education in primary schools. Third, the TPB postulates three conceptually independent determinants of intentions (i.e., ATB, SN, and PBC). These factors have accounted for a large proportion of the variances in the variables of many previous studies. This study, however, did not include SN as a variable. Future research should investigate SN as a potential facilitating condition (Mei et al., 2018). Fourth, this study measured PBC using only self-efficacy towards AI. Rhodes and Courneya's (2004) study discovered that adding a phrase "If I wanted to" to such items could influence the effects of ATB, SN and PBC on BI. It is suggested that this phrase should be included in the items in the future. Future studies can also consider including control items that can affect PBC.

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