So, H. J. et al. (Eds.) (2020). Proceedings of the 28th International Conference on Computers in Education. Australia: Asia-Pacific Society for Computers in Education

Primary students' readiness for learning of artificial intelligence: A case study in Beijing

Ching Sing CHAI[a], Pei-Yi LIN[a*], Morris Siu-Yung JONG[ab], Yun DAI[a] & Thomas CHIU[ab]
[a] *Department of Curriculum and Instruction &* [b] *Centre for Learning Sciences and Technologies*
The Chinese University of Hong Kong, Hong Kong

Abstract: Recent advances in artificial intelligence (AI) has aroused attention among educators to consider including it in K-12 teaching. Several curricula have been developed, and some schools have begun testing the curriculum. Within such a context, it is important to study and investigate students' readiness to learn AI. This study includes students' motivation to learn AI, perceived relevance of AI, anxiety about current or future development of AI to predict students' AI readiness. A questionnaire-based survey composed of these factors was designed. A sample of 107 primary students from Beijing, China was used to provide initial evidence about the validity and reliability of the questionnaire. The findings support that the questionnaire has adequate construct validity and acceptable reliability. In addition, the findings indicate that students have intrinsic motivation and career motivation. They also perceive the relevance of AI and regard themselves are ready for an AI-empowered future.

Keywords: artificial intelligence, readiness, motivation, relevance, anxiety

1. Introduction

Artificial intelligence (AI) has been viewed as the next effective tools to enhance teaching and learning. AI educational research has been focused on AI development and applications (for a review, see Roll & Wylie, 2016). For instance, an intelligent tutoring system (Ma, Adesope, Nesbit, & Liu, 2014), an adaptive learning system (Nakic, Granic, & Glavinic, 2015), and such AI technologies are used in K-12 and university education settings to support learning. Beyond education, AI is an emerging technology and AI applications have pervasive influences in all areas. AI is also developed as a new curriculum to be learned in K-12 settings. Given the background, a fundamental question arises: how to promote students' readiness to learn AI? Current AI learning research has not sufficiently explored primary students learning about AI.

Technology readiness reflects an individual's willingness to leverage new technologies to accomplish tasks (Parasuraman, 2000). Investigations of students' technology readiness reflect how curricula are preparing students to live and thrive with the technology. This would usually entail studying how psychological factors associated with curriculum design contribute to the students' sense of readiness. Strong curriculum design needs to enhance students' motivation to learn (Yilmaz, 2017) and establish relevance of learning for students (Jong, 2014, 2020). These conditions, when met, help students to learn about specific technology and thus build their readiness. In the case of AI, strong curriculum design would also need to reduce students' fear of AI (Wang & Wang, 2019) and promote a possibility for students to choose AI engineering as a future career choice. Surveying these variables that influence students' readiness allows educators to refine the teaching and learning strategies used to promote students' readiness to learn AI. This study considered the potential effects of intrinsic motivation, career motivation, perception of relevance of AI, and AI anxiety on students' readiness in the AI learning context when primary students were introduced to AI curriculum.

2. Literature review

2.1. AI readiness

AI readiness refers to the construct of technology readiness (Parasuraman, 2000) to unpack students' propensity to learn AI. Meanwhile, readiness is an important variable in indicating student learning mediated with or by technologies, if students are more techno-ready, they will tend to engage in technology learning and seek technology-related professions (Parasuraman & Colby, 2015). Past research indicates students technology readiness is an essential variable to ascertain students preference to learn new technologies (e.g., e-learning, see Gay, 2016; mobile learning, see Cheon et al., 2012; game-based learning, see Jong et al., 2006). AI has widened the scope of learning in education by adopting AI technology. AI readiness construct can be viewed as an overall state of mental processes resulting from how students' predisposition to learn AI as learning content (Lin, Shih, & Sher, 2007). This study refers to technology readiness index confirmed by Parasuraman (2000), and adapts items to measure students' readiness to learn AI.

2.2. Motivation for AI learning

Learning motivation is an important factor to explain the process that people invest in learning activities and to explain their willingness to engage in a learning environment (Jong et al., 2010; Shang et al., 2006). Students' readiness is identified by types of motivations, attitudes, and behaviors in a computer-supported collaborative learning environment (Xiong, So, & Toh, 2015). In other words, motivations for AI learning could be viewed as a component of measuring students' readiness to engage in AI learning. Ryan and Deci (2000) indicated that intrinsic motivation is an element attached to learning processes. An individual is intrinsically motivated when (s)he feels interesting, gains pleasure and satisfaction from completing or working on a challenge. Extrinsic motivation is related to an individual's desire to succeed and achieve certain goals (Ryan & Deci, 2000). That is, increased student motivations will enhance willingness to learn AI technologies. In the present study, we measure students' intrinsic motivation to learn AI out of curiosity and interest. Extrinsically career motivation associated with AI learning, on the other hand, should include students' career decisions and behaviors, such as searching for and accepting a job. Past motivation study has shown that students' level of e-learning readiness and motivation are associated (Yilmaz, 2017). In this study, both intrinsic and extrinsic motivations are assumed to predict AI readiness.

2.3. Relevance of AI

Relevance refers to that a person perceives learning content meets his/her needs or desires (Keller. 2000). Students who perceive AI learning content is personally relevant or is connected to their goals will be motivated to participate in AI learning. That is, if students feel the AI learning content is meaningful, or recognize the importance of AI will help them achieve personal goals, motives, and values, then they will be motivated to learn AI. Relevance can also be understood pedagogically as a factor that illustrates people's actual experiences when they can relate prior knowledge and experiences to the current content they learned, and when the content can be applied on their jobs or in real life (Keller, 2010). Park, Nam, and Cha' study (2012) pointed out that when university students found that mobile learning was relevant to their study and future career, they tended to use mobile to learn. In the context of AI learning, relevance of AI refers to students' ability to connect the AI learning content as something useful or meaningful to them. When students see the connections between what they need to know about AI and what AI learning will bring to them, they will learn more about AI, and this will thus build their readiness for an AI-empowered world.

2.4. AI anxiety

AI anxiety refers to an effective response of feeling of fear being expressed about out-of-control AI (Johnson & Verdicchio, 2017). Past research indicated that people's fear and insecurity towards technologies influence people's adoption of technologies. This study includes AI anxiety to understand the impact of advanced AI technology on students' readiness for the AI-empowered future. As AI technology will certainly transform how we live and work, people will be required to learn in-demand knowledge and update their skills in order to remain relevant and meet future career needs (Korinek & Stiglitz, 2017). Meanwhile, they may feel anxious toward AI when they perceive that AI technology will change or eliminate jobs and create new ones (Wang & Wang, 2019). Previous research on ICT anxiety was found to have a relation to students and educators' use of mobile learning (Mac Callum, Jeffrey, & Kathryn, 2014). In addition, technology may cause students to feel anxious because they had negative or inadequate experience in learning to use the technology (Keller, 2010). Similarly, anxiety toward AI technology may influence its uses. As a result, this study assumed that self-perceived fear about AI technology would have a negative influence on people's sense of readiness to learn AI.

2.5 Gender Differences

Lee, Chai and Hong (2019) review of existing STEM research indicates that gender differences are an important issue for STEM-related disciplines, which is echoed in some recent related literature (e.g., So et al., 2020). AI, as a discipline, is situated within the field of engineering and the design of AI applications depends much on the engineers' knowledge about science and mathematics. It is likely that there may be gender differences between students when they learn about AI. Hence, this study also investigates gender differences among the students.

In sum, this study examines the following two research questions: (1) Is the 5-factor AI learning model reliable and valid? (2) Do the variables, i.e., intrinsic and extrinsic motivations, relevance of AI and AI anxiety predict primary students AI readiness? (3) Are there gender differences among the measured variables?

3. Method

3.1. Participants

The current sample included 107 students who were participated in AI learning in Beijing, China. They were third to sixth graders from two primary schools. The sample included 57 females and 50 males with an overall mean age of 9.08 (SD = 0.72). The mean hours spent on AI-learning and projects were 6.75 (SD = 3.09). The AI curriculum covered AI developments and applications such as the history of AI, image and voice recognition, content recommendation, machine learning, and ethical issues. At the end of the semester, the participants were informed about the purpose of the anonymous survey, and participation was voluntary. They were instructed to respond to each item by choosing the response that accurately described their level of agreement.

3.2. Instruments

This study included five subscales: (1) intrinsic motivation subscale was adapted from motivated strategies for learning questionnaire (MSLQ) – intrinsic goal orientation (Pintrich, Smith, Garcia, & McKeachie, 1991) (4 items; e. g., "In the AI class, I prefer course material that arouses my curiosity, even if it is difficult to learn."). (2) Career motivation subscale was adapted from Glynn, Taasoobshirazi, and Brickman (2009) (3 items; e.g., "I think about how learning AI can help me get a good job."). (3) Relevance of AI subscale were selected and modified from Keller's (2010) the Instructional Materials Motivation Survey and the Course Interest Survey (6 items; e. g., "The things I am learning in this AI class will be useful to me."). (4) AI Anxiety subscale was modified from MSLQ – test anxiety (Pintrich et al., 1991) (5 items; e. g., "When I consider the capabilities of AI, I think about how difficult my future will be. "). (5) AI readiness subscale was selected and modified from Parasuraman's (2000) technology readiness index, we adapted 6 items in the present study (e. g., AI products and services that use the newest technologies are much more convenient to use.). The items in the questionnaires were presented on a 4-point Likert scale (1 = *strongly disagree*; 4 = *strongly agree*). After experts in AI-learning reviewed the first draft of these items, school teachers were invited to review the questionnaires and provided their feedbacks. The final versions of the questionnaire were then confirmed.

3.3. Data analysis

Exploratory factor analysis (EFA) was employed to examine the 5-factor AI learning model. The principal axis factoring was utilized as the extraction method, along with the rotation method of direct oblimin. The alpha reliabilities of the scales were generated to check reliability. Correlation and regression analysis were then conducted to examine whether predictors: intrinsic motivation, career motivation, relevance of AI, and AI anxiety factors could predict AI readiness (outcome variable).

4. Results

4.1. Exploratory Factor Analysis of the Measurement Model

As shown in Table 1, a total of 18 items were retained in the final version of the measurement. Six items with cross-loadings were omitted and five factors were revealed: ‘intrinsic motivation’ (IM), ‘career motivation’ (CM), ‘relevance of AI’ (R), ‘AI anxiety’ (A), and ‘AI readiness’ (RE). Items factor loading ranged from 0.46 to 0.93. The total variance explained was 70.47%. Cronbach’s alpha coefficient of these factors was around 0.81 – 0.95 for each scale, and the overall reliability was 0.80, which revealed high reliability of these factors, suggesting that the internal consistency was sufficient for statistical analysis. Table 1 presents the results of descriptive statistics and EFA.

Table 1. *EFA of measured items*

	M	SD	α	Factor loading	% of variance
1.Intrinsic motivation (IM)	3.51	0.64	0.85	0.46 - 0.65	3.20
2. Career motivation (CM)	3.46	0.63	0.88	0.67 - 0.82	38.99
3.Relevance (R)	3.55	0.57	0.81	0.47 - 0.84	4.44
4.Anxiety (A)	2.25	1.09	0.95	0.79 - 0.93	18.78
5.Readiness (RE)	3.62	0.49	0.83	0.56 - 0.92	5.06

4.2. Correlation Analysis among the Subscales

The Pearson correlation coefficients between the factors were calculated to explore the relationship between students’ perceptions of AI learning motivations, relevance of AI, AI anxiety and AI readiness. The intrinsic motivation, career motivation, relevance of AI, and AI readiness were significantly and positively related (from $r = 0.55$ to $r = 0.65$, $p < .001$). AI anxiety was significantly and negatively related to intrinsic motivation ($r = -0.21$, $p < .05$), relevance of AI ($r = -0.26$, $p < .001$) and AI readiness ($r = -0.20$, $p < .05$). The results of correlation analysis provided initial support for the relationships between the measured factors.

4.3. Predicting students’ readiness to learn AI

The linear regression analysis was conducted to predict students’ readiness to learn AI. The results showed that intrinsic motivation was the strongest predictor for all the factors ($\beta = 0.32$, $p < 0.01$), relevance of AI and career motivation are equally contributing to AI readiness ($\beta = 0.23$, $p < 0.05$). The findings indicate that the students’ motivations for learning AI and their perception of the relevance of AI provided 43.8% explanation, and these variables are very important predictors for students’ readiness for AI learning and technology.

4.4. Gender differences among measured variables

Independent t-tests were employed to compare male and female students' perceptions of AI readiness, motivation for AI learning, relevance of AI, and AI anxiety. Male students significantly possessed greater career motivation (t = 2.66, p < .01) and readiness (t = 3.30, p < .01) for AI than female students. There were no significant gender differences among intrinsic motivation (t = 1.48, p > 0.5), relevance of AI (t = 1.81, p > 0.5) and AI anxiety (t = 1.05, p > 0.5). This suggests that male students were more likely to be ready for AI, and they have greater career motivation to engage in AI professions than female students.

5. Discussion

The rapid growth of AI technology will push educational institutions to adopt relevant AI curriculum. There is a need to understand what factors will influence students' readiness for AI learning. Based on our survey, we validated a questionnaire with the five factors including intrinsic and career motivations for AI learning, perceptions of relevance of AI, AI anxiety and AI readiness, and explored the relationships among these factors. This study provides the following findings. First, the survey indicates that the questionnaire about students' AI learning with five factors demonstrated satisfactory reliability with construct validity. This indicated that it is an acceptable instrument to assess students' readiness to learn AI. This study incorporated five factors, and they were successfully maintained through EFA.

Second, according to the initial research findings, the analyses highlight that intrinsic and career motivations, relevance of AI predict students' readiness. Meanwhile, AI anxiety did not significantly predict AI readiness. The results imply that students who are more intrinsically and extrinsically motivated to learn AI, and who perceived AI as relevant to them, are readier for an AI-empowered world. Previous research indicated that motivation is an important factor for teachers' readiness to integrate technology in teaching and learning (Copriady, 2014), and students' motivation toward e-learning is one of the component of e-learning readiness (Yilmaz, 2017). This study provides evidence that motivations are important factors in predicting students' AI readiness. Few studies attempted to adopt relevance of technology as a predictor in a technology-based learning environment (Chai et al., in press; Dai et al., 2020; Park et al., 2012). This study considered relevance of AI is an essential factor in the AI learning context, and the finding showed that relevance of AI significantly predicted students' AI readiness. Our findings may offer AI course designers and instructors a means for examining their courses in terms of motivational design, relevance and corresponding effects on enhancing students' readiness. They may also need to pay attention to possible gender differences.

Acknowledgements

We appreciate the support of the school principals given to the study, as well as the participation of the teachers and students in the experiment.

References

Chai, C.S., Lin, P. Y., Jong, M. S. Y., Dai, Y., Chiu, T. K. F., & Qin, J. (2020). Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students. *Journal of Educational Technology & Society*, in press.

Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & education*, *59*(3), 1054-1064.

Copriady, J. (2014). Self-Motivation as a Mediator for Teachers' Readiness in Applying ICT in Teaching and Learning. *Turkish Online Journal of Educational Technology-TOJET*, *13*(4), 115-123.

Dai, Y., Chai, C. S., Lin, P. Y., Jong, M. S. Y., Guo, Y., & Qin, J. (2020). Promoting Students' Well-Being by Developing Their Readiness for the Artificial Intelligence Age. *Sustainability*, *12*(16), 6597.

Gay, G. H. (2016). An assessment of online instructor e-learning readiness before, during, and after course delivery. *Journal of Computing in Higher Education, 28*(2), 199-220.

Glynn, S. M., Taasoobshirazi, G., & Brickman, P. (2009). Science motivation questionnaire: Construct validation with nonscience majors. *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching*, *46*(2), 127-146.

Johnson, D. G., & Verdicchio, M. (2017). AI anxiety. *Journal of the Association for Information Science and Technology*, *68*(9), 2267-2270.

Jong, M. S. Y. (2014). Elementary students' view of collaborative knowledge building in LearningVillages. *Interaction Design and Architecture(s), 21*, 37–56.

Jong, M. S. Y. (2020). Promoting elementary pupils' learning motivation in environmental education with mobile inquiry-oriented ambience-aware fieldwork. *International Journal of Environmental Research & Public Health*, *17*(7), Article 2504.

Jong, M. S. Y., Shang, J. J., Lee, F. L., & Lee, J. H. M. (2010). An evaluative study on VISOLE—Virtual Interactive Student-Oriented Learning Environment. *IEEE Transactions on Learning Technologies, 3*(4), 307–318.

Jong, M. S. Y., Shang, J. J., Lee, F. L., Lee, J. H. M., & Law, H. Y. (2006). *Learning online: A comparative study of a game-based situated learning approach and a traditional web-based learning approach*. In Z. Pan, R. Aylett, H. Diener, X. Jin, S. Gobel, & L. Li (Eds.), Lecture notes in computer science: Technologies for e-Learning and digital entertainment (pp. 541–551). Heidelberg: Springer.

Keller, J. M. (2000). How to integrate learner motivation planning into lesson planning: The ARCS model approach. *VII Semanario, Santiago, Cuba*, 1-13.

Keller, J. M. (2010). The ARCS model of motivational design. In *Motivational design for learning and performance* (pp. 43-74). Springer, Boston, MA.

Korinek, A., & Stiglitz, J. E. (2017). *Artificial intelligence and its implications for income distribution and unemployment* (No. w24174). National Bureau of Economic Research.

Lee, M. H., Chai, C. S., & Hong, H. Y. (2019). STEM Education in Asia Pacific: Challenges and Development. *The Asia-Pacific Education Researcher, 28***,** 1–4.

Lin, C. H., Shih, H. Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. *Psychology & Marketing, 24*(7), 641-657.

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901-918.

Mac Callum, K., Jeffrey, L. & Kathryn. (2014). Comparing the role of ICT literacy and anxiety in the adoption of mobile learning. *Computers in Human Behavior*, *39*, 8-19.

Nakic, J., Granic, A., & Glavinic, V. (2015). Anatomy of student models in adaptive learning systems: A systematic literature review of individual differences from 2001 to 2013. *Journal of Educational Computing Research, 51*(4), 459-489.

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of service research*, *2*(4), 307-320.

Park, S. Y., Nam, M. W., & Cha, S. B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British journal of educational technology*, *43*(4), 592-605.

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of service research*, *18*(1), 59-74.

Pintrich, P. R., Smith, D. A. F., Garcia, T. & McKeachie, W. J. (1991). *A Manual for the use of the motivated strategies for learning*. Michigan: School of Education Building, The University of Michigan.

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582-599.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. Contemporary educational psychology, 25(1), 54-67.

Shang, J. J., Jong, M. S. Y., Lee, F. L., & Lee, J. H. M. (2006). VISOLE: A new game-based situated learning paradigm. *Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies* (pp. 1082–1083). Kerkrade, Netherlands.

So, H. J., Jong, M. S. Y., & Liu, C. C. (2020). Computational thinking education in the Asian Pacific region. *The Asia-Pacific Education Researcher*, *29*(1), 1–8.

Wang, Y. Y., & Wang, Y. S. (2019). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 1-16.

Xiong, Y., So, H. J., & Toh, Y. (2015). Assessing learners' perceived readiness for computer-supported collaborative learning (CSCL): A study on initial development and validation. *Journal of Computing in Higher Education, 27*(3), 215-239.

Yilmaz, R. (2017). Exploring the role of e-learning readiness on student satisfaction and motivation in flipped classroom. *Computers in Human Behavior*, *70*, 251-260.