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Developing and validating an artificial intelligent empowerment instrument: evaluating the impact of an artificial intelligent literacy programme for secondary school and university students

Siu-Cheung Kong * and Yin Yang

*Correspondence:
sckong@eduhk.hk
siucheungkong@gmail.com
Department of Mathematics and Information Technology,
The Education University of Hong Kong,
Hong Kong SAR
Full list of author information is available at the end of the article

Abstract

Artificial intelligence (AI) is rapidly transforming various sectors of society, requiring a new form of literacy: AI literacy. This study validated a new instrument designed to measure students' AI empowerment conceptualised as consisting of four components: impact, self-efficacy in AI, creative self-efficacy in AI, and meaningfulness. Confirmatory factor analysis was used to validate the proposed components of the AI empowerment instrument. The sample comprised 224 secondary school and university students who completed an 18-hour AI literacy programme. The results showed that the students' AI empowerment was significantly increased by the AI literacy programme. Specifically, the AI literacy programme was found to narrow the gender gap in AI empowerment. Furthermore, the results highlighted that prior programming experience did not significantly affect AI empowerment, indicating that AI literacy can be achieved regardless of programming experience. This study provides a theoretical framework for understanding and quantifying the extent to which individuals feel empowered after engaging with AI activities for its conceptual understanding. It provides educators with a tool to measure students' understanding and confidence in their AI abilities. The study also suggests directions for future research.

Keywords: Artificial intelligence literacy, Artificial intelligence empowerment, Instrument, Evaluation, Secondary school and university students

Introduction

Artificial intelligence (AI) is becoming increasingly ubiquitous in various aspects of society (Dai et al., 2020; Southworth et al., 2023) and is gaining much attention in education (Luckin et al., 2022). AI is a powerful and transformative technology that can bring a multitude of benefits and challenges to society (Dwivedi et al., 2021). However, it also raises ethical questions related to privacy, fairness, data protection, and security (Burton et al., 2017; Hwang et al., 2020).

Discussions about the potential replacement of humans by AI have been going on for several years (Dwivedi et al., 2021; Pinto dos Santos et al., 2019; Shuaib et al., 2020). Some scholars have expressed concerns that AI may soon surpass human intelligence and capabilities (Shuaib et al., 2020). Others have argued that AI will never be able to replicate human creativity, emotions, and values, emphasising that humans will always maintain a unique role and advantage in society (Pinto dos Santos et al., 2019; Shabbir & Anwer, 2018). These contrasting views echo the simultaneous overestimation and underestimation of the power of AI, highlighting the urgent need to increase students' AI literacy. AI literacy includes understanding the basic concepts and applications of AI, its ethical considerations, and its social implications (Kong et al., 2022; Kong et al., 2023a; Kong et al., 2023b). By developing their AI literacy, students are better equipped to navigate the opportunities and risks of AI, preparing them for an increasingly AI-saturated future (Dai et al., 2020; Kong et al., 2023b; Luckin et al., 2022).

AI literacy education has received increasing global attention in recent years (Kong et al., 2022; Kong et al., 2023a; Kong et al., 2023b; Su et al., 2023) and several design frameworks have been proposed for designing AI literacy programmes for K–12 education (Ng et al., 2022; Yang, 2022) and higher education (Kong et al., 2022; Southworth et al., 2023). However, studies have shown that many AI literacy courses focus on enhancing students' basic AI knowledge and skills (Ng et al., 2023), paying less attention to students' affective dimensions such as their attitudes, motivation, and confidence in using AI (Rizvi et al., 2023). Moreover, research has shown that AI literacy programmes for non-technical learners are still in their infancy (Xu & Babaian, 2021) and few studies have discussed curriculum design for AI literacy (Su & Yang, 2022). Therefore, curriculum design is one of the challenges faced by educators when engaging in the development and implementation of AI literacy for students.

In this study, an AI literacy programme emphasising conceptual development was implemented to foster students' AI empowerment. Conceptual development pertains to the understanding of the core concepts and principles of machine learning in this study, such as supervised learning, unsupervised learning, deep learning, neural networks, and computer vision (Kong et al., 2023b). The programme implemented in this study aimed to equip students with AI literacy, enabling them to better respond to the use of AI in daily life, and to inspire students to explore the potential and challenges of AI in their own fields and interests. In this study, we defined AI empowerment as occurring when students (1) see the effect of completing the task(s) using AI, (2) are confident in using AI, (3) believe they can use AI creatively to provide solutions to address real-world problems, and (4) view the purpose of a task involving AI as meaningful.

Considering the status quo of research in the field of AI literacy, in which very few instruments have been developed to measure AI empowerment among secondary school and university students, little is known about how an AI literacy programme involving conceptual development can foster student' AI empowerment. This study validated a questionnaire to assess AI empowerment and evaluated the effect of the proposed AI literacy programme on students' AI empowerment. We also examined how demographics such as gender and prior programming experience affect AI empowerment. To this end, the following three research questions were addressed.

1. Research Question 1: What are the dimensions and indicators of students' AI empowerment?
2. Research Question 2: To what extent does an AI literacy programme developing conceptual understanding of machine learning affect students' AI empowerment?
3. Research Question 3: To what extent are demographics such as gender and prior programming experience related to AI empowerment?

Literature review

What is empowerment?

Empowerment is broadly defined as a multidimensional social process that enables individuals to take control of their lives (Luechauer & Shulman, 1993; Page & Czuba, 1999; Perkins & Zimmerman, 1995). Luechauer and Shulman (1993) defined empowerment as 'the humanistic process of adopting the values and practicing the behaviours of enlightened self-interest so that personal and organizational goals may be aligned in a way that promotes growth, learning, and fulfilment' (p. 13). This process encourages individuals to use their power to address issues they consider important, both in their personal lives and in their community and society. One of the most influential theories of empowerment in organisational psychology is the theory developed by Thomas and Velthouse (1990), which suggests that empowerment is a cognitive construct that consists of four dimensions: sense of impact, competence, meaningfulness, and choice. According to this model, individuals feel empowered when they perceive that their actions significantly affect the outcomes of their work, they possess the skills and abilities necessary to perform their tasks effectively, their work aligns with their personal values and goals, and they enjoy autonomy and discretion in their working methods (Lee & Koh, 2001; Liden et al., 2000; Seibert et al., 2011). These four elements are interrelated and mutually reinforcing, creating a positive feedback loop that enhances individuals' motivation, satisfaction, and performance (Seibert et al., 2011; Thomas & Velthouse, 1990). Central to the theory of empowerment is the idea that providing individuals with the necessary resources, skills, and opportunities can enhance their sense of motivation, leading to an increased sense of well-being and life satisfaction (Spence Laschinger et al., 2010; Zimmerman, 2000).

Thomas and Velthouse's (1990) empowerment framework has been widely applied in business management, political, and educational contexts. In the educational context, for example, Frymier et al. (1996) validated this empowerment model in two empirical studies and identified three dimensions in measuring learner empowerment: impact, competence, and meaningfulness. The lack of a choice dimension could be due to students' limited authority to choose in the classroom. Typically, teachers determine the learning curriculum and activities, which contrasts with work environments where employees may have greater autonomy in their tasks (Thomas & Velthouse, 1990).

Why is it important to understand AI empowerment?

AI has transformed the way people interact with technology, disrupting traditional industries and creating new opportunities for innovation (Laupichler et al., 2022). In recent years, the concept of AI empowerment has emerged as an important area of research, focused on harnessing the potential of AI to enable individuals and organisations to achieve their goals more effectively (Kong et al., 2022; Kong et al., 2023b). Several AI literacy programmes have been developed to improve AI empowerment (e.g., Kong et al., 2022; Kong et al., 2023a; Laupichler et al., 2022). A primary objective of AI literacy programmes is to empower students to become active and key participants in the digital society, whether in K–12 education (Kong et al., 2023a; Su et al., 2023), higher education (Kong et al., 2023b; Ouyang et al., 2022), or workplace learning (Frick et al., 2021; Schwendicke et al., 2020). Several studies have explored the relationship between AI empowerment and student outcomes, with many reporting positive effects (Ouyang et al., 2022; Yue et al., 2022). AI empowerment can be developed as students engage in learning experiences that enable them to comprehend AI concepts, use AI applications, and critically evaluate the ethical and social implications of AI.

How is AI empowerment built?

Building upon prior theories of empowerment, Kong et al. (2018) proposed a model of empowerment in the context of computational thinking education. This framework includes four essential dimensions: impact, self-efficacy, creative self-efficacy, and meaningfulness. To start with, teaching students about AI's potential for positive and negative impacts can motivate them to develop responsible AI systems. Understanding the impact also prepares them to anticipate the ethical concerns related to AI tools (Kong et al., 2021; Kong et al., 2024).

As AI becomes increasingly prevalent, having the confidence to engage with these systems is crucial for students to be successful in a technology-driven world. This confidence directly influences their ability to learn and apply AI concepts effectively (Chong et al., 2022). Despite the concerns raised that young students might struggle to distinguish between AI self-efficacy and creative self-efficacy, the importance of believing in one's ability to innovate is illustrated by Cropley and Cropley (2010). They argued that without the belief in their capability to effect change, individuals are unlikely to feel motivated to create new and effective solutions. Echoing this, Tierney and Farmer (2002) highlighted that creative self-efficacy, the belief in one's ability to produce original ideas, is a crucial skill that should be emphasized in educational settings, particularly in teaching AI literacy (Puozzo & Audrin, 2021; Wang et al., 2023). Creative self-efficacy is vital in AI literacy education as it empowers students to believe in their ability to develop innovative solutions using AI technologies. The goal of AI literacy education, as stated by Yau et al. (2023), is to develop individuals who are not only users of AI but also contributors to the field. This involves designing new AI systems and applications that can have a beneficial impact on society. AI literacy education that incorporates creative self-efficacy encourages a problem-solving mindset that is essential for addressing the unique challenges posed by AI technologies. Finally, when students perceive their learning activities as meaningful, their engagement and motivation increase significantly. In AI education, connecting the learning content to real-life applications and ethical implications makes the learning experience more relevant and valuable (Kong et al., 2021; Kong et al., 2024; Luckin et al., 2022).

Thus, the empowerment model proposed by Kong et al. (2018) is thus not only applicable but also imperative in AI literacy education. It equips students not just with the technical skills required to operate AI applications but also with the creativity to innovate and the ethical grounding to ensure their impacts are positive. The following explains the four dimensions in this study.

First, 'impact' refers to learners' perceptions of AI's influence on society and daily life, focusing on their understanding of AI literacy and its societal effects (Dwivedi et al., 2021). Enhancing students' AI literacy empowers them to recognise AI's potential impact on the future, providing a basis for their engagement in AI-related tasks (Holmes et al., 2022).

Second, 'AI self-efficacy' refers to the belief in one's ability to perform the actions necessary to address future AI-related challenges (Bandura, 1982; Frymier et al., 1996; Hong, 2022). According to Bandura (1982), self-efficacy is the belief in one's ability to achieve desired goals. In educational environments, self-efficacy is defined as students' personal judgment of their capability to successfully complete learning tasks or achieve designated educational objectives (Han & Geng, 2023). Research has showed that the perceived self-efficacy of technology use is closely linked to their positive attitude that they can successfully perform tasks (Han et al., 2017; Han & Geng, 2023). Recent empirical evidence supports the importance of AI self-efficacy in the adoption and use of AI technologies (Hong, 2022; Kwak et al., 2022). For example, Hong (2022) found that people with higher AI self-efficacy were more likely than others to adopt AI technologies. Similarly, Kwak et al. (2022) found that participants' self-efficacy in using AI in nursing predicted their behavioural intentions to use AI technologies. This further underscores the importance of AI self-efficacy in facilitating the acceptance and implementation of AI in education.

Third, 'creative self-efficacy' is defined as 'a belief in one's ability to produce creative outcomes' (Tierney & Farmer, 2002, p. 1138). This concept stems from Bandura's (1997) broader notion of self-efficacy in a specific context. The development of creative self-efficacy has been shown to have a profound impact on individuals' creative performance (Tierney & Farmer, 2002). Individuals with high creative self-efficacy are more likely than others to be confident in their ability to generate novel ideas (Du et al., 2020) and persevere in the face of setbacks or obstacles (Yang et al., 2017).

Finally, 'meaningfulness' refers to learners' perceptions of the importance or value of tasks (Frymier et al., 1996). If learners perceive learning tasks as meaningful, they are likely to invest time and effort in acquiring the necessary skills and knowledge to complete the tasks (Meng et al., 2020). This sense of meaningfulness can lead to feelings of empowerment when learners recognise their potential to make a significant impact through the expertise gained.

Research design

Course design

This study was part of a larger project aimed at enhancing students' AI literacy through an AI literacy programme for secondary school and university students in Hong Kong. The course design was guided by the AI literacy framework proposed by Kong et al. (2023b, 2024), including four aspects: cognitive, metacognitive, affective, and social dimensions. The course was designed with 18 hours face-to-face workshops on machine learning in Course 1 (9 hours) and deep learning learnt in Course 2 (9 hours) to develop their foundational concepts of machine learning. These two courses aimed to enhance their understanding of the AI concepts of machine learning (e.g., what AI is, the five steps of machine learning, supervised learning, unsupervised learning) and deep learning (e.g., neural networks, computer vision, convolution neural networks, and recurrent neural networks). Lectures provided theoretical knowledge, while hands-on learning activities and group discussions encouraged practical application and critical thinking. Collaborative learning activities were also incorporated to allow participants to explore the real-life applications of AI in diverse contexts. This detailed course design and instructional process ensured that students not only grasped the theoretical aspects of AI but also gained practical experience and insight into its societal implications.

Participants

Two hundred and twenty-five students from Hong Kong were recruited to participate in the three courses. A total of 224 responses were obtained (one student who did not complete the survey was excluded from the formal analysis). Among the participants, 65.6% were senior secondary school students (n = 146, Secondary 4 = 49, Secondary 5 = 48, Secondary 6 = 49) and 34.8% were university students (n = 78). In terms of gender distribution, 49.6% (n = 111) were female. Regarding the students' prior programming experience, most of the students (n = 144) reported having prior programming experience.

Instrument

An AI empowerment survey was conducted and validated in this study. This section discusses the development of the AI empowerment instrument and associated items in two phases. In the first phase, an item pool was developed based on the literature (Kong & Lai, 2022; Kong et al., 2022; Kong et al., 2023a; Kong et al., 2023b) and focus group interviews. The panel of experts included one professor specialising in AI literacy education, one academic coordinator of the study, two associate professors at the university of the study, and five senior secondary school teachers. Drawing on an existing empowerment questionnaire (Kong et al., 2018), 17 candidate items were extracted and organised according to the following four constructs: (1) impact, referring to students' perception of the impact of AI and the importance of AI literacy (four items); (2) AI self-efficacy, referring to students' belief that they have the necessary skills and abilities to use AI (five items); (3) creative self-efficacy in AI, referring to students' belief in using AI to produce novel ideas and solutions to real-world problems (four items); and (4) meaningfulness, referring to students' perceptions of the value of AI (four items).

The second phase involved translation of the questionnaire using the back-translation method (Brislin, 1986). Three bilingual researchers of the study participated in this process. Two researchers independently translated the instrument into Chinese, discussing and resolving any discrepancies between the English and Chinese versions. The third researcher then translated the Chinese version into English, which was compared with the original instrument to confirm accuracy and quality.

After the translation process, the expert panel evaluated the questionnaire items in terms of wording, comprehensibility, relevance, and sequence, considering any factors that could constrain participants' responses. Next, a pilot study was conducted with 45 students who were not involved in the survey reported in this study. One item with a factor loading less than 0.5 was removed (Hair et al., 2010), resulting in the final AI empowerment instrument consisting of 16 items across four constructs. The survey items were rated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Detailed information on the AI empowerment instrument can be found in Appendix.

Data collection

The data for this study were collected from the students who completed Course 1 and Course 2. To examine the impact of the AI literacy programme on their perceptions of AI empowerment, their views were collected before Course 1 and after Course 2. Before data collection, ethical approval to collect data in this study was granted by the Human Research Ethics Committee of the university (Ref. no. A2020-2021-0204 and 2021-2022-0325) and consent forms were signed by the participants. The survey was distributed via the online tool Qualtrics (https://www.qualtrics.com/).

Data analysis

A confirmatory factor analysis (CFA) of the AI empowerment instrument was first conducted, then the effectiveness of the three AI literacy courses on AI empowerment among secondary school and university students was evaluated. The data analysis was divided into two parts.

First, CFA was conducted to assess the measurement validity of the multi-item scale (i.e., impact, self-efficacy in AI, creative self-efficacy in AI, and meaningfulness) among the 224 participants who completed the AI literacy programme. CFA with maximum likelihood estimation was performed for each subscale using IBM SPSS Amos 28.0. The four factors proposed in this study (i.e., impact, self-efficacy in AI, creative self-efficacy in AI, and meaningfulness) were assumed to be correlated. All items with a factor loading greater than 0.5 were considered to load strongly on their respective factors (Hair et al., 2010). Multiple criteria were used to evaluate the model. The fit of a model with a comparative fit index (CFI) and Tucker–Lewis index (TLI) of at least 0.95 (Bentler, 1990) and a root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR) not exceeding 0.05 is considered excellent (Mueller & Hancock, 2010). In contrast, a model with CFI and TLI values of at least 0.90 and RMSEA and SRMR values not exceeding 0.08 is considered to have adequate fit (Byrne, 2010). Finally, reliability, convergent validity, and discriminant validity were assessed.

The level of reliability of each construct was evaluated using Cronbach's alpha (α) to assess the internal consistency of their respective items (Cronbach's $\alpha > 0.7$) (Cronbach, 1951). Convergent validity was assessed using average variance explained (AVE) and composite reliability (CR). A satisfactory level of convergent validity is indicated by an AVE value greater than 0.5 or a CR value greater than 0.7 (Fornell & Larcker, 1981; Hair et al., 2010). Discriminant validity demonstrates the extent to which a construct is distinct from other constructs. This test was used to determine whether the four factors of AI empowerment were distinct from each other. An AVE value greater than the squared correlations suggests adequate discriminant validity between the factors (Fornell & Larcker, 1981). Two CFA models were estimated: a first-order model to validate the measurement of the first-order factors and a second-order model to examine whether all the factors fitted the general concept of AI empowerment. Cronbach's α was calculated for the full AI empowerment instrument and for each subscale to determine their internal consistency.

Regarding the evaluation of the programme, a Wilcoxon signed-rank test was conducted to compare the direction and magnitude of the ranked mean differences between the pre- and post-surveys (Portney & Watkins, 2015). In addition, a Mann–Whitney U test was used to compare two independent samples when the data are interval scale, but the assumptions of the *t*-test (normality) are not satisfied (McCrum-Gardner, 2008). Effect size reveals the magnitude of an effect when the difference between variables is significant. We used eta squared, which classifies effect sizes as small (0.02), moderate (0.13), and large (0.26) (Cohen et al., 2013).

Results

Validation of the AI empowerment instrument

Dimensions and indicators of AI empowerment

Table 1 presents the CFA model fit indices of the one-factor model with all 16 items loading on a single factor, the correlated four-factor model, and the second-order four-factor model. Because the chi-square statistic (χ^2) is sensitive to large sample sizes, its significance implied an inadequate fit of the models (all models' $p < 0.001$) (Curran et al., 1996). However, the other fit indices showed that unlike the one-factor model and the correlated four-factor model, the second-order four-factor model fitted the data acceptably.

Table 1 Model fit indices for the subscales of AI empowerment

Model	χ^2	*df*	*p*	χ^2/df	CFI	TLI	SRMR	RMSEA
One-factor	522.437	104	0.000	5.023	0.878	0.859	0.054	0.134
Correlated four-factor	266.038	98	0.000	2.715	0.951	0.940	0.038	0.088
Second-order four-factor	221.944	97	0.000	2.288	0.964	0.955	0.037	0.076

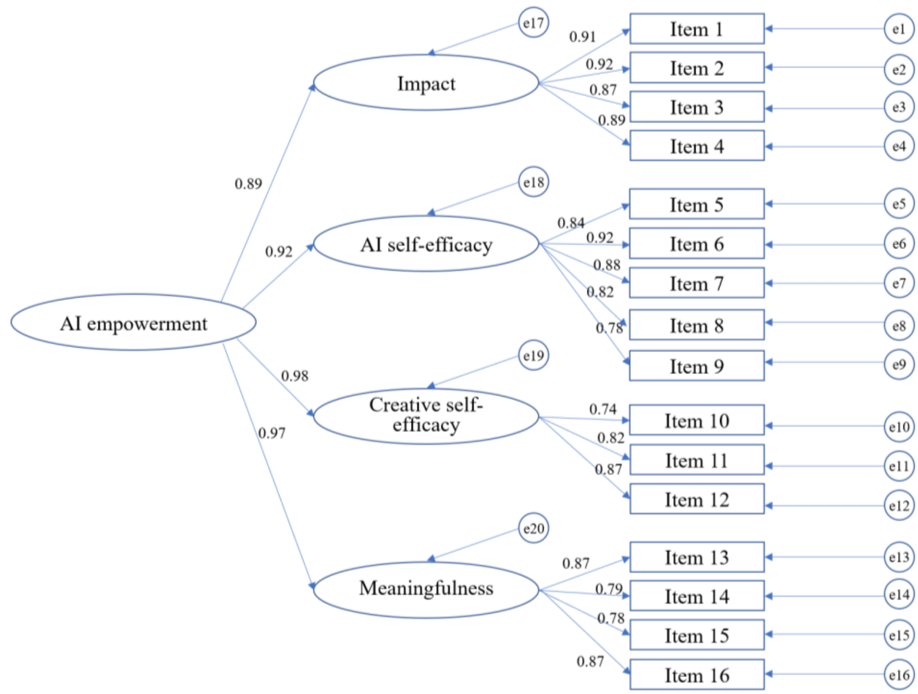

Fig. 1 Second-order four-factor model of AI empowerment

Note. For brevity, errors are not reported after applying standardised regression weights.

Figure 1 shows the structure of the correlated four-factor model and the coefficients for each path. The second-order four-factor model of AI empowerment and the correlated four-factor model with all 16 items loading on a single factor were compared. The fit indices indicated that the second-order four-factor model fitted the data better than the correlated four-factor model (χ^2/df = 2.288 < 2.715; CFI = 0.960 > 0.951; TLI = 0.955 > 0.940; RMSEA = 0.076 < 0.088). As shown in Table 1, the values of the incremental fit indices (e.g., CFI, TLI, and RMSEA) of the current instrument reached the recommended threshold, supporting the appropriateness of the proposed model.

Figure 1 shows the second-order four-factor model and the coefficients for each path. In the second-order four-factor model, the factor loadings of the second-order factors ranged from 0.89 to 0.97, while the item loadings on the second-order factors ranged from 0.74 to 0.92. All of the parameters were significant ($p < 0.001$). The factor loadings (standardised factor loadings) of the observed variables were all above the recommended value of 0.60 (Hair et al., 2010). Therefore, the second-order four-factor model of AI empowerment was validated.

Reliability and validity

Table 2 shows the reliability and convergent validity results. Regarding reliability, Cronbach's α values for each factor were all greater than 0.800 (from 0.833 to 0.944),

Table 2 Reliability and convergent validity results of the four-factor model of AI empowerment

Construct	Standardised factor loadings	S.E.	CR (*t*-value)	*p*	SMC	CR	AVE	Reliability
I1 Impact	.915				0.837	0.945	0.810	0.944
I2 Impact	.921	.042	23.402	***	0.848			
I3 Impact	.869	.045	19.990	***	0.755			
I4 Impact	.895	.043	21.557	***	0.801			
I5 AI self-efficacy	.844				0.712	0.915	0.684	0.914
I6 AI self-efficacy	.816	.081	14.997	***	0.666			
I7 AI self-efficacy	.876	.071	16.884	***	0.767			
I8 AI self-efficacy	.822	.077	15.187	***	0.676			
I9 AI self-efficacy	.775	.080	13.854	***	0.601			
I10 Creative self-efficacy	.739				0.546	0.851	0.656	0.876
I11 Creative self-efficacy	.820	.065	16.387	***	0.672			
I12 Creative self-efficacy	.866	.086	13.518	***	0.750			
I13 Meaningfulness	.866				0.750	0.897	0.686	0.833
I14 Meaningfulness	.792	.062	14.672	***	0.627			
I15 Meaningfulness	.783	.071	14.422	***	0.613			
I16 Meaningfulness	.868	.066	14.277	***	0.753			

Note. I = Item, S.E. = standard error, CR = composite reliability, SMC = squared multiple correlations, AVE = average variance extracted. **p* < .05; ***p* < .01; ****p* < .001.

indicating good internal consistency. Specifically, Cronbach's α was 0.944 for impact, 0.914 for self-efficacy, 0.876 for creative self-efficacy, and 0.833 for meaningfulness, and 0.966 for the full AI empowerment instrument.

Regarding convergent validity, the AI empowerment instrument showed adequate convergent validity. The CR values ranged from 0.851 to 0.945, all above the recommended threshold of 0.70 (Fornell & Larcker, 1981; Hair et al., 2010). The AVE values of the four factors were all greater than 0.50 (from 0.656 to 0.810), which show the good convergent validity.

Evaluation of the effect of the AI literacy programme on AI empowerment

Table 3 shows the descriptive statistics and Wilcoxon signed-rank test results for AI empowerment among secondary school and university students according to the four factors of AI empowerment. The results showed that after completing the AI literacy programme, the students' perceived impact of AI (z = 3.03, $p < 0.05$), perceived self-efficacy in AI (z = 6.54, $p < 0.001$), perceived creative self-efficacy in AI (z = 3.15, $p < 0.001$), and perceived meaningfulness of AI (z = 3.43, $p < 0.05$) increased significantly.

Table 3 Descriptive statistics and Wilcoxon signed-rank test results for AI empowerment before and after completing the AI literacy programme

Construct	Before Programme (n = 224)		After Programme (n = 224)		Wilcoxon signed-rank test	
	M	*SD*	*M*	*SD*	*z*	Sig. (two-tailed)
Impact	4.17	.54	4.27	.54	3.03	.002**
AI self-efficacy	3.84	.61	4.07	.57	6.54	.000***
Creative self-efficacy	4.05	.59	4.16	.55	3.15	.002**
Meaningfulness	4.09	.56	4.20	.54	3.43	.001**
AI empowerment	64.36	8.23	66.67	8.12	5.65	.000***

Note. **p* < .05; ***p* < .01; ****p* < .001; *M* = mean, *SD* = standard deviation.

Effect of gender

Regarding the effect of gender on AI empowerment among secondary school and university students, a Mann–Whitney U test was conducted to compare the AI empowerment scores between male and female students before and after the programme. Table 4 shows the descriptive statistics and Mann–Whitney U test results for AI empowerment between male and female students before and after completing the AI literacy programme.

The results showed that there was a significant difference in AI empowerment between male and female students before the programme (U = 8,056.50, z = 3.71, $p < 0.001$), with female students having lower scores than their male counterparts. However, this difference disappeared after the programme (U = 6,995.00, z = 1.50, $p = 0.134$), indicating that the AI literacy programme had a positive effect on reducing the gender gap.

Effect of prior programming experience

Regarding the effect of prior programming experience on students' AI empowerment, a Mann–Whitney U test was conducted to compare the AI empowerment scores between students with prior programming experience and those without such experience before and after the programme.

Table 5 summarises the descriptive statistics and the Mann–Whitney U test results for the two groups. The results showed that the programme was equally effective for the two

Table 4 Descriptive statistics and Mann–Whitney U test results for AI empowerment among male and female students before and after completing the AI literacy programme

Item		Male (n = 113)		Female (n = 111)		Mann–Whitney U test		
		M	*SD*	*M*	*SD*	U	*z*	*p*
Total	Before	65.11	8.60	63.59	7.79	8,056.50	3.71	0.000***
	After	68.42	8.43	64.89	7.43	6,995.00	1.50	0.134

Note. *p < .05; **p < .01; ***p < .001; *M* = mean, *SD* = standard deviation.

Table 5 Descriptive statistics and Mann–Whitney U test results for AI empowerment among students with prior programming experience and those without such experience

Item	With prior programming experience (n = 144)		Without prior programming experience (n = 80)		Mann–Whitney U test		
	M	*SD*	*M*	*SD*	U	*z*	*p*
PreTotal	63.93	8.37	65.13	7.95	5,414.00	-0.749	0.454
Impact	4.14	.59	4.14	.59	5,938.00	0.400	0.689
AI self-efficacy	3.94	.67	3.94	.67	6,641.00	1.923	0.054
Creative self-efficacy	3.72	.67	3.72	.67	6,652.00	1.994	0.046
Meaningfulness	3.99	.60	3.99	.60	6,494.00	1.644	0.100
PostTotal	66.21	8.14	67.51	8.07	5,210.00	-1.19	0.235
Impact	4.30	.51	4.21	.61	6,228.50	1.982	0.279
AI self-efficacy	4.20	.49	4.10	.63	6,018.50	0.568	0.570
Creative self-efficacy	4.09	.55	4.03	.60	6,302.00	1.231	0.218
Meaningfulness	4.23	.53	4.14	.56	6,285.50	1.170	0.242

Note. M = mean, *SD* = standard deviation.

groups of students, regardless of their background knowledge. There was no significant difference in AI empowerment between students with and without prior programming experience before (U = 5,413.00, z = -.749, p = 0.454) or after (U = 5,210.99, z = -.1.19, p = 0.235) the programme. This result implies that programming experience is neither a prerequisite nor a barrier to AI empowerment and is consistent with the AI literacy programme's goal of promoting AI empowerment and literacy among students from diverse disciplines and backgrounds.

Discussion

In this study, we validated a survey instrument designed to measure AI empowerment and examined the effectiveness of the proposed AI literacy programme in enhancing AI empowerment among secondary school and university students. The results showed that the two courses of the AI literacy programme were effective in enhancing the students' AI empowerment in terms of impact, AI self-efficacy, creative self-efficacy, and meaningfulness. The two courses for enhancing their conceptual understanding of machine learning were found to facilitate AI empowerment. In the future, when developing AI literacy programmes, AI tasks should be designed to allow students to perceive their importance and meaningfulness. These tasks should also be designed with an optimal level of difficulty to maintain and enhance students' self-efficacy and creative self-efficacy in using AI.

This study further examined how demographics such as gender and prior programming experience influence AI empowerment. The results showed that the AI literacy programme significantly reduced the gender gap in AI empowerment, with female students showing significant gains after the programme. Previous research has indicated a gender gap in the field of AI, with fewer women than men participating and advancing in AI-related careers (Nuseir et al., 2021). This gap is often attributed to various factors, such as limited access to resources and social and cultural biases in the field (Luengo-Oroz et al., 2021). Consequently, women may have less confidence in their ability to understand and use AI technologies, leading them to feel less empowered by AI. To address these disparities, this study proposed an AI literacy programme focused on understanding AI concepts. The two courses of this programme aimed to equip students with essential AI-related knowledge and skills. After the completion of the two courses of the AI literacy programme, the gender gap in AI empowerment narrowed significantly. Specifically, the female participants showed significant gains in their AI empowerment. This finding indicates that the AI literacy programme is effective in providing women with the knowledge and skills needed to better understand the AI technologies. The programme may also boost women's confidence and interest in the AI field. These results are consistent with those of Kong et al. (2022), who also found that the AI literacy programme helped narrow the gender gap in AI empowerment among university students.

In addition to the gender gap, the influence of students' prior programming experience on their AI empowerment was examined. The results showed that AI empowerment did not depend exclusively on prior programming experience, underscoring the universality and versatility of the AI literacy programme. This result is consistent with those of recent studies indicating that prior programming knowledge does not significantly affect the level of AI empowerment (Kong et al., 2022; Kong et al., 2023a; Kong et al., 2023b). This implies that AI literacy and empowerment do not necessarily depend on prior programming skills, which challenges the common assumption that a strong background in programming is a prerequisite for understanding and using AI effectively (Xu & Babaian, 2021; Yue et al., 2022).

Conclusion and implications

In this study, an instrument for assessing AI empowerment in young adults was developed and validated. Furthermore, an evaluation study was conducted. The results demonstrated that a well-structured AI literacy programme, encompassing a conceptual introduction to general machine learning and then deep learning can significantly boost AI empowerment among young adults. This approach also led to an increase in the students' perception of the impact of AI, their self-efficacy, creative self-efficacy in using AI, and their perceived value of AI and its meaningfulness. The results also showed the potential of the AI literacy programme to narrow the gender gap in AI empowerment, such that individuals, regardless of their prior programming experience, can be empowered by AI through the AI literacy programme.

The study has both theoretical and practical contributions to AI education. First, the development of a new instrument to measure AI empowerment provides a theoretical framework for understanding and quantifying the extent to which individuals feel equipped to engage with AI. This instrument can help to refine existing theories of AI empowerment. Second, the study provides empirical evidence supporting the effectiveness of the proposed AI literacy programme in enhancing AI empowerment. Furthermore, the two courses of the programme narrow the gender gap and encourage those with no prior programming experience to engage in the field of AI. By empowering a broader demographic with AI, we can promote greater diversity and inclusivity in the field, which is essential for creating more comprehensive and empathetic AI solutions. Future studies should therefore integrate AI applications and conceptual knowledge to facilitate AI literacy among diverse learners. The insights gained from the proposed AI literacy programme can guide future curriculum design, thereby fostering a more inclusive AI community.

Despite these contributions, the study has two main limitations. First, this study only included secondary school and university students from Hong Kong. Therefore, more diverse participants, particularly from other cultural contexts, should be considered in future studies. A notable limitation of the study is that while it encompassed both secondary school and university students, it did not explicitly differentiate between the developmental and educational stages of these two groups. Secondary school and university students are at different cognitive, emotional, and social development stages, which might affect how they perceive and benefit from informational and emotional support. Future studies should consider segmenting these groups to explore age-specific and educational context-specific variations in how support influences self-efficacy. Second, this study relied on self-reported data. Future studies could use learners' artefacts and qualitative data to measure their perceptions and experiences, which could help to better understand effective AI empowerment.

Appendix: AI Empowerment Instrument

Impact

Item 1: I want to apply my AI knowledge and skills to solve problems in daily life.

Item 2: I want to solve problems with AI to make people's lives better.

Item 3: I want to solve problems with AI to make daily life easier.

Item 4: I want to apply my AI knowledge and skills to develop interesting solutions to problems.

AI self-efficacy

Item 5: I can learn to be better at solving problems with AI.

Item 6: I am good at solving problems with AI.

Item 7: I think of myself as someone who can solve problems with AI.

Item 8: I have the knowledge and skills to solve problems with AI.

Item 9: I have confidence in my ability to solve problems with AI.

Creative self-efficacy

Item 10: I can think creatively when I use AI to solve problems.

Item 11: Solving problems with AI gives me an opportunity to be creative.

Item 12: I like to express my ideas through solving problems with AI.

Meaningfulness

Item 13: Using AI to solve problems will help me achieve my goals.

Item 14: I want to be good at solving problems with AI.

Item 15: Using AI to solve problems is important to me.

Item 16: Using AI to solve problems is useful to me.

Abbreviations

AI: Artificial intelligence; AVE: Average variance explained; CFA: Confirmatory factor analysis; CFI: Comparative fit index; CR: Composite reliability; RMSEA: Root mean square error of approximation; SRMR: Standardised root mean square residual; TLI: Tucker–Lewis index.

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Authors' contributions

The authors are responsible for the whole manuscript.

Authors' information

Prof. Siu-Cheung Kong is the Research Chair Professor of Department of Mathematics and Information Technology, The Education University of Hong Kong, Hong Kong SAR. Dr. Yin Yang is the Lecturer II of Department of Mathematics and Information Technology, The Education University of Hong Kong, Hong Kong SAR.

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