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Developing and validating a scale of empowerment in using artificial intelligence for problem-solving for senior secondary and university students

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ABSTRACT

Empowerment enables students to be psychologically and affectively ready to leverage the benefits of artificial intelligence (AI). However, a theory-driven scale to extend empowerment into the use of AI for problem-solving is lacking. This study developed and validated an 11-item scale of empowerment in using AI for problem-solving (EUAIPS) based on a proposed conceptual framework that synthesises empowerment and AI-related literature. The EUAIPS scale encompasses impact, self-efficacy, and meaningfulness in using AI for problem-solving. We collected data from a diverse sample of Hong Kong senior secondary and university students before (N = 477) and after the course (N = 409). Results demonstrated that the EUAIPS scale with a three-factor structure had good reliability and validity. Students also felt significantly more empowered to use AI for problem-solving after a 14-h course using AI for problem-solving. These findings empirically support the affective dimension of AI literacy and show that psychological control/competence is particularly important for students to harness AI to solve problems at the affective level. This study presents a valid instrument for researchers and practitioners to measure empowerment in using AI for problem-solving and informs AI literacy curriculum designers about including learning activities to help students realise its impact, self-efficacy, and meaningfulness.

1. Introduction

Artificial intelligence (AI) has rapidly integrated into our daily lives, and people from all walks of life need to know what it is and how to make good use of it in this AI-permeated world (Kong et al., 2024; Long & Magerko, 2020). According to Long and Magerko (2020), AI literacy encompasses a range of competencies and skills that enable individuals to evaluate, communicate, and effectively utilise AI in various settings, including workplaces and homes. Mere conceptual knowledge of AI principles is insufficient for fully leveraging AI's capabilities; individuals should apply AI to address real-world challenges across diverse scenarios (Chiu et al., 2022).

Using AI for problem-solving stands as a crucial element of AI literacy, exerting a profound influence on individuals' educational experiences, professional endeavours, and personal lives. The application of AI for problem-solving also aligns with the prevailing contemporary trend in educational settings that emphasise learning through problem-solving (Chiu et al., 2022; Hornberger et al., 2023; VanLehn et al., 2020; Wang & Lester, 2023). Therefore, individuals should be emotionally and psychologically prepared to harness the advantages of using AI for problem-solving (Chiu et al., 2022; Kong et al., 2024; Popenici & Kerr, 2017).

Recent research shows a growing interest in the affective dimension of AI literacy and how students harness AI for problem-solving at the affective level (Joksimovic et al., 2022). Some research indicates that empowerment, a perceived control or motivation-based construct, increases students' psychological readiness, confidence, and trust to leverage AI's power to resolve real-life problems (Chiu et al., 2022; Conger & Kanungo, 1988; Frymier et al., 1996; Kong et al., 2024). However, a theory-driven instrument that relates empowerment to using AI for problem-solving is still lacking. Hence, this study aims to develop and validate an empowerment in using AI for problem-solving (EUAIPS) scale.

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2. Literature review

2.1. AI literacy, problem-solving, and empowerment

Several definitions of AI literacy that vary in the precise number and configuration of AI competencies frameworks for various target groups have been published recently. One of the most widely used definitions put forward by Long and Magerko (2020), who define AI literacy as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (p. 2). Ng et al. (2021) conceptualised AI literacy as four core aspects: Knowing and understanding AI, using and applying AI, evaluating and creating AI, and AI ethics. They underlined that students should not merely be inculcated with the concepts behind technology but also know how to use AI applications and be aware of the potential ethical issues related to AI to become responsible citizens.

Laupichler et al. (2023) proposed a working definition of AI literacy for non-experts (e.g., individuals without formal AI or computer science education), describing AI literacy as encompassing competencies involving basic knowledge, the analytical evaluation of AI and the critical application of AI technologies by non-experts. Later, Kong et al. (2024) proposed the AI literacy framework with four dimensions: cognitive dimension (understanding AI concepts), metacognitive (using AI for problem-solving), affective dimension (psychological readiness to use AI), and social dimension (ethics of problem-solving with AI). This framework emphasises that rather than merely having a conceptual understanding of AI concepts, educated citizens need to be involved in the meta-cognitive process of applying AI tools through solving real-life problems.

Solving problems that resemble real-life situations is dynamic, could have multiple solutions, and require multidisciplinary teamwork, which is often recognised as a critical component of computer science education (Dörner, 1980; Kunze et al., 2018; Wang et al., 2018). Opportunities for AI supporting such complex problem-solving are conceptualised as three interconnected domains of cognitive, affective, and social processes (Joksimovi et al., 2023). Complex problem-solving can induce the arousal of affective states (e.g., fun, social anxiety), attitudes, trust, confidence, salience, and morals.

Empowerment is defined as the process of creating intrinsic task motivation that increases one's self-efficacy and energy through providing environment and tasks (Conger & Kanungo, 1988; Thomas & Velthouse, 1990). Spreitzer (1995) viewed empowerment as a psychological mechanism enabling individuals to gain control of their lives, which is necessary to generate such behavioural outcomes. Luechauer and Shulman (1993) postulated that empowerment is a "humanistic process of adopting the values and practising behaviours of enlightened self-interest so that personal and organisational goals may be aligned in a way that promotes growth, learning and fulfilment" (p. 10). The aforementioned conceptualisations of empowerment all emphasise a motivational base. Thus, we do believe empowerment plays a crucial role in cultivating individuals' psychological readiness to interact with AI and enhancing their problem-solving capabilities at the affective level in the learning context (Kong et al., 2024; Joksimovi et al., 2023).

2.2. Using AI for problem-solving

There is a growing emphasis on developing students' competencies in using AI for problem-solving, which represents the metacognitive aspect of AI literacy in secondary and higher education (Kong et al., 2023, 2024; Zhang & Aslan, 2021). The project-based learning (PBL) approach, which involves students in solving real-world problems and creating artefacts, models, or solutions, has been widely utilised to enhance students' AI learning experiences (Kong et al., 2022; Lu & Fan, 2023; Vargas et al., 2020). PBL is collaborative and student-centred, requiring students to document and present their PBL outcomes to demonstrate how they utilise AI for problem-solving (Blumenfeld et al., 1991; Saengrith et al., 2022; Vargas et al., 2020). The research conducted by Scharick et al. (2024) explored the usability of human-robot collaboration by simulating real-world scenarios based on a robotic system, demonstrating that the integration of AI technology must prioritise human-centred AI, good usability, and accessibility, ensuring the successful adoption and utilisation of AI by a diverse range of people regardless of technical expertise.

Silapachote and Srisuphab (2017) orchestrated a problem-solving-centric interactive course tailored for computer science and engineering undergraduates, integrating strategic games and AI components. The outcomes indicated that students could enhance their comprehension of AI and refine their problem-solving abilities through collaborative puzzle-solving, strategic gaming, and intellectual exchanges. In alignment with the transition from a technology-centric to an interdisciplinary approach in AI education within higher education, universities have also embarked on integrating AI into the curricula of non-computer science disciplines, including teacher education, medicine, mathematics, psychology, and music (Kong et al., 2021; Ng et al., 2021, 2023).

Despite the acknowledged importance of AI metacognitive support for problem-solving, a growing interest has been paid to the affective dimension of AI literacy (Kong et al., 2024; Ng et al., 2024). That is to say, the successful leverage of AI for problem-solving is also linked to students' psychological readiness, confidence, or attitudes towards human-AI interactions (Chiu et al., 2022; Kong et al., 2024; Nuary et al., 2022). Luckin et al. (2022) presented a 7-step training programme to cultivate psychological AI readiness, finding that psychologically AI-ready university students and instructors tended to make the best decisions about which AI products or services were the most effective for problem-solving and how to leverage AI to their advantage. Having confidence in AI performance increases interaction and collaboration between humans and AI (Kong et al., 2024; Ng et al., 2024). Joksimovic et al. (2022) also indicated that AI should support humans in complex problem-solving at the social (e.g., cooperation, collaboration, ethics of using AI) and affective (e.g., confidence, psychological readiness) levels.

2.3. Empowerment in using AI for problem solving

Empowerment is seen as an 'enabling' process, whereby individuals gain control of their lives and issues that concern them (Bandura, 1989; Conger & Kanungo, 1988; Rappaport, 1987). The multidimensional nature of empowerment focuses mainly on personally experienced psychological cognition and manners and is broadly accepted in the literature (Frymier et al., 1996; Menon, 1999; Spreitzer, 1995; Thomas & Velthouse, 1990). Thomas and Velthouse (1990) conceptualised a cognitive model of empowerment that motivates a person's behaviour in each task situation: impact, competence/self-efficacy, meaningfulness, and choice. Spreitzer (1995) also defined four components to examine the psychological experience of empowerment involved with cognitive and motivational elements: meaning, competence/self-efficacy, impact, and self-determination, which serve as an important part of facilitating such behavioural outcomes. In an identical vein, Menon (1996) considered 'perceived control', 'competence/self-efficacy', and 'goal internalisation' as three vital facets underlying the construct of empowerment. These conceptualisations of empowerment originated in the workplace context to explore the relationship between manager and employee.

Frymier et al. (1996) first defined learner empowerment in the instructional context, including impact, competence, and meaningfulness. Frymier et al. (1996) excluded the dimension of 'self--determination' because the researchers believed that although it operated well in superior-subordinate relationship contexts, it was irrelevant in the educational context. Specifically, employees are likely to control their work or work units based on previous training and experience in the workplace, while students have less willingness and

power to expect or exercise self-determined activities in the classroom (e.g., grading criteria and task requirements), which are predominated and controlled by teachers (Frymier et al., 1996; Spreitzer, 1995). Therefore, the current study did not examine students' self-determination, as students, to some extent, rely on external agents (e.g., teacher feedback and group collaboration) that provide scaffolding for their use of AI in problem-solving within the PBL context.

Regardless of the theoretical frameworks around empowerment proposed by different scholars, each framework consistently underscores three critical components of empowerment: impact, self-efficacy, and meaningfulness. As most conceptualisations and frameworks of empowerment highlight a motivational foundation, the concept is equally relevant to the teacher-student relationship within learning contexts (Luechauer & Shulman, 1993). Empowered individuals are often motivated to perform tasks and exercise control of those tasks that hold mutual value for themselves and their peers, promoting alignment between values and actions in feeling empowered and acting in an empowered manner. Explicitly speaking, impact and self-efficacy reflect the perceived control/competence of one's learning and learning unit manifested in empowerment, while meaningfulness captures the essence of empowerment: the motivation to control (Bandura, 1989; Frymier et al., 1996; Spreitzer, 1995; Zimmerman, 1995). According to the planned theory of behaviour, perceived control (i.e., empowerment) plays a central role in shaping the intention to perform or change behaviours (e.g., using AI for problem-solving). In addition, affective needs (confidence, self-efficacy) are a crucial aspect of AI literacy development (Chiu et al., 2022; Kong et al., 2024). One's subjective assessment of competencies (e.g., self-efficacy) and positive attitudes towards AI (e.g., meaningfulness/impact) can boost acceptance of, confidence in, and intention of using AI for problem-solving (Joksimovic et al., 2022; Kwak et al., 2022; Latikka et al., 2019; Wagner & Sherwood, 1969).

Following a literature synthesis, we propose that when using AI for problem-solving, empowered students tend to (1) perceive the impact on professional life and social development, (2) feel competent/self-efficacious to perform using AI for problem-solving and (3) find using AI for problem-solving to be meaningful. Hence, we argued that empowerment in using AI for problem-solving includes the following: the impact of using AI for problem-solving (IP), self-efficacy in using AI for problem-solving (SE), and meaningfulness in using AI for problem-solving (MN). These three psychological traits reflect the multi-dimensional nature of empowerment in the AI context. The following paragraphs detail these aspects.

2.4. Impact of using AI for problem-solving

Impact in using AI for problem-solving refers to students' perception of the extent to which one's behaviour (e.g., using AI) makes a difference to the outcomes of accomplishing tasks (e.g., problem-solving), that is, yielding intended strategic, administrative, or operating effects of AI-task environments (Frymier et al., 1996; Thomas & Velthouse, 1990). The more impact a student believes that using AI for problem-solving will produce, the more motivated they will become to use it (Tang & He, 2023). The widespread application of AI in universities dramatically impacts students' psychological control over academic challenges by providing flexible, cost-effective, and scalable solutions for simple and complex tasks (Jia & Tu, 2023; Zawacki-Richter et al., 2019). University students can obtain personalised learning support and opportunities (e.g., online courses, adaptive learning systems, and virtual tutors to benefit their lifelong learning) from various AI-powered platforms (Nuary et al., 2022). Once individuals are equipped with knowledge, skills, and resources to use AI for problem-solving, they are more able to navigate an AI-prevalent world, thereby driving social development (Kong et al., 2021; Nuary et al., 2022).

2.5. Self-efficacy in using AI for problem-solving

Self-efficacy or perceived competence is the second component of empowerment (Conger & Kanungo, 1988; Frymier et al., 1996; Spreitzer, 1995; Thomas & Velthouse, 1990). Self-efficacy in using AI for problem-solving refers to one's belief in his or her competence to use AI for problem-solving, which is analogous to personal mastery. High levels of self-efficacy in using AI for problem-solving enable students to persist in solving problems if barriers appear (Frymier et al., 1996; Sun & Yang, 2023). Self-efficacy also predicts university students' problem-solving skills, and frequent interactions with AI enhance students' self-efficacy and alleviate their stress levels (Jia & Tu, 2024; Lisak et al., 2022). Thus, university students with higher self-efficacy are more likely to embrace new AI technology, perceive the usefulness of AI and be proficient in its use, and apply it in problem-solving (Wang & Chuang, 2024; Wang, King, et al., 2023). Self-efficacy also mediated the relationship between university students' AI capabilities and critical thinking. Thus, it is vital for universities to develop AI-based programmes, which should be tailored to students' needs and offer immediate feedback to make students feel self-efficacious about their capability to use AI to solve problems (Jia & Tu, 2024).

2.6. Meaningfulness in using AI for problem-solving

Meaningfulness in using AI for problem-solving refers to students' perceived value of using AI for problem-solving based on their beliefs, ideas, and standards (Frymier et al., 1996; Sun & Yang, 2023). The more meaningful a student perceives using AI to be for solving a series of real-life problems, the more commitment, involvement, and concentration they will invest in accomplishing problem-solving projects (Frymier et al., 1996; Wang et al., 2018). Some researchers hold that human-AI collaboration affects an individual's sense of meaningfulness and influences their learning engagement and satisfaction, especially in team-based learning structures (Luckin et al., 2022; Sadeghian et al., 2024).

Students' perception of the meaningfulness of using AI for problem-solving is linked to their views on task integrity, task significance, autonomy, skill cultivation and use, and individual belongingness (Bankins & Formosa, 2023; Sadeghian et al., 2024). For instance, AI can build people's independence by helping them handle mundane tasks and freeing their time for more engaging and challenging activities (Bankins & Formosa, 2023). Using AI for problem-solving gave students a greater sense of meaningfulness, and it is more appealing than just supervising AI and confirming its actions (Sadeghian et al., 2024). This was because students contributed more directly to the tasks and had effective dialogue with the AI collaborator in the interactive paradigm; by contrast, AI users felt incompetent and perceived a lack of autonomy, as well as associated negative emotions, in the supervisory paradigm.

2.7. Current research on assessing AI literacy

A growing number of research have explored the development of AI literacy tests or scales. Some AI literacy tests focus on course-specific knowledge or evaluation (e.g., Chiu et al., 2024; Lin et al., 2024; Ng et al., 2022; Rodríguez-García et al., 2021; Zhang et al., 2023), while Hornberger et al. (2023) developed and validated a multiple-choice AI literacy test targeting students' general understanding of AI with a large sample of German university students. Self-reported scales are believed to be suitable for examining students' attitudes, values, and beliefs in social and behavioural science through a non-evaluative manner due to their cost-effectiveness, versatility, and good external validity (Couper & Miller, 2008; Dörnyei & Taguchi, 2009).

To our best knowledge, there are several well-known scales to measure AI literacy in secondary and higher education (e.g., Carolus et al., 2023; Kim & Lee, 2022; Ng et al., 2024; Wang et al., 2022). Karaca et al. (2021) designed a 27-item Medical Artificial Intelligence

Readiness Scale for Medical Students (MAIRS-MS) with four dimensions: cognition, ability, vision, and ethics. Wang, Rau, and Yuan (2023) developed another AI literacy scale (AILS) built on the information communication technology (ICT) framework, which included four subscales of awareness, usage, evaluation, and ethics with good psychometric properties. However, these two scales lack consideration of theoretical advancements in the conceptualisation of AI literacy (Ng et al., 2021) and fail to emphasise individuals' ability to use AI for problem-solving. Another AI literacy scale was developed and validated by Kim and Lee (2022) for primary school students, characterised by the social impact of AI, the understanding of AI, AI execution plans, problem-solving with AI, data literacy, and AI ethics. This scale removed many items whose factor structure had been changed and supplemented during the developmental process.

Recently, some researchers have embarked on paying attention to the affective and psychological perspectives of AI literacy (Carlous et al., 2023; Ng et al., 2024; Wang & Chuang, 2024), in addition to emphasising the behavioural, cognitive, and ethical dimensions of AI literacy. The Meta AI literacy scale (MAILS) was developed by Carlous et al. (2023) by integrating four theoretical concepts from Ng et al. (2021) and the subjective assessment of one's competencies (e.g., self-efficacy) from the psychological perspective and other competencies such as problem-solving, emotion regulation in responses to adverse effects of AI. However, this MAILS did not refer to the factorial structure through cross-validation. Ng et al. (2024) also developed and validated a 32-item self-reported questionnaire on AI literacy (AILQ) incorporating the identified competencies in four dimensions: (1) affective learning (intrinsic motivation and self-efficacy/confidence), (2) behavioural learning (behavioural commitment and collaboration), (3) cognitive learning (know and understand; apply, evaluate and create) and (4) ethical learning among Hong Kong secondary school students. Nonetheless, the AILQ give more priority to students' efficacy in learning AI rather than how they use AI for problem-solving at the psychological and affective levels.

2.8. The research gap

The planned theory of behaviour indicates that perceived behaviour control (e.g., empowerment), subjective assessment of one's competence (e.g., self-efficacy), and attitudes (e.g., meaningful/impact for using AI) lead to intentions of generating or changing AI-used behaviours (Ajzen, 1985; Joksimovic et al., 2022; Kwak et al., 2022; Wagner & Sherwood, 1969). Empowerment is a multi-dimensional construct for creating intrinsic task motivation, which has been extensively investigated over decades and is further conceptualised as the affective dimension of AI literacy (Kong et al., 2024). Empowerment influences individuals' psychological readiness, engagement, and confidence in AI (Joksimovic et al., 2022; Luckin et al., 2022). Moreover, affective engagement with AI and how AI supports students in solving problems at the affective level (e.g., students' confidence, self-efficacy, and attitudes) is still under-researched despite the increasing attention directed at the effectiveness of AI for problem-solving. This gap is particularly notable in studies involving both senior secondary and university students.

Existing instruments for AI literacy are not entirely suited to understanding how students utilise AI for problem-solving considering the desiderata described above (see the section "Current research on assessing AI literacy). Simultaneously, the current empowerment scales are primarily situated in workplace contexts (e.g., Thomas & Velthouse, 1990) or educational settings (e.g., Frymier et al., 1996; Sun & Yang, 2023). There are no scales for evaluating students' empowerment within AI contexts. While some researchers have developed scales addressing AI self-efficacy or attitudes (Park et al., 2024; Schepman & Rodway, 2020; Wang & Chuang, 2024), these typically capture only a single dimension of empowerment, which is widely regarded as a multidimensional construct. Hence, there is a notable absence of theory-driven instruments that connect empowerment to the use of AI for problem-solving by incorporating the metacognitive and affective dimensions of AI literacy (Kong et al., 2024; Ng et al., 2024).

To situate the current research in the 'using AI for problem-solving' context, we proposed a conceptual framework of empowerment in using AI for problem-solving: empowered students are more likely to perceive the impacts of using AI for problem-solving, feel self-efficacious to perform using AI for problem-solving, and recognise the meaningfulness of using AI for problem-solving. Building on our proposed conceptual framework, this study aims to develop a self-report EUAIPS scale and explore whether students feel empowered to use AI for problem-solving after a course. Hence, this study addresses the following questions:

RQ1: What is the factor structure of the EUAIPS scale? Is measurement invariance across gender established?
RQ2: What is the validity and reliability/internal consistency of the resulting EUAIPS scale?
RQ3: To what extent do senior secondary and university students feel empowered to use AI for problem-solving after a course adopting the PBL approach?

3. Methodology

3.1. Course implementation

This study constitutes the third part (Course 3) of an AI literacy programme, which recruited students publicly from 32 secondary schools and a university in Hong Kong. Course 1 and Course 2, each comprising of 9-h learning activities, covered basic concepts of machine learning and deep learning, respectively. The entire programme was free of charge and non-credit-bearing. These courses were taught by teachers with academic qualification of either a doctoral degree, master's degree, or postgraduate diploma in related disciplines.

This AI literacy course is a capstone project of AI application development using the PBL approach comprising 14-h learning activities. Students enrolled in this course had attended the first two courses (Kong et al., 2022, 2024), so they had a basic understanding of machine learning. In this study, students were required to develop an AI problem-solving project using five steps of machine learning as a guideline (Kong et al., 2024). Prior to this course, the students were provided with self-directed reading materials before introductory lectures, both of which illustrated some real-life scenarios where AI applications could be used, as well as considerations concerning ethical principles and issues (e.g., fairness of AI, beneficence of AI, and human autonomy) when designing and using AI models (Kong et al., 2022, 2024). Afterwards, students participated in a group AI project to solve problems using various AI-powered platforms that were available freely or via institutional subscription.

To be specific, the group project consisted of five steps. (1) Students identified a problem that the following AI-powered platforms could solve, and the teachers demonstrated how to use them (e.g., Google Teachable Machine for image, sound, and posture recognition; Microsoft Azure QnA Maker for creating chatbots and Microsoft Azure Machine Learning Studio for generating quantitative data analysis and prediction). (2) The teachers carried out individual project consultations about the takeaway messages and reiterated the five steps of machine learning, which students were required to use as a guideline to design AI-based solutions. (3) The teachers asked students to think about the ethical implications of their AI-based solutions and how potential ethical concerns could be mitigated if they appeared. (4) The students doped out their AI-based solutions for their self-defined problems during the 6-h collaborative project work, including collecting data, training AI models for obtaining solutions, reflecting on encountered challenges and possible improvements, and ethical considerations in relation to their AI-based solutions. (5) Finally, the students demonstrated their AI-based solutions in group project presentations, and they assessed their peers

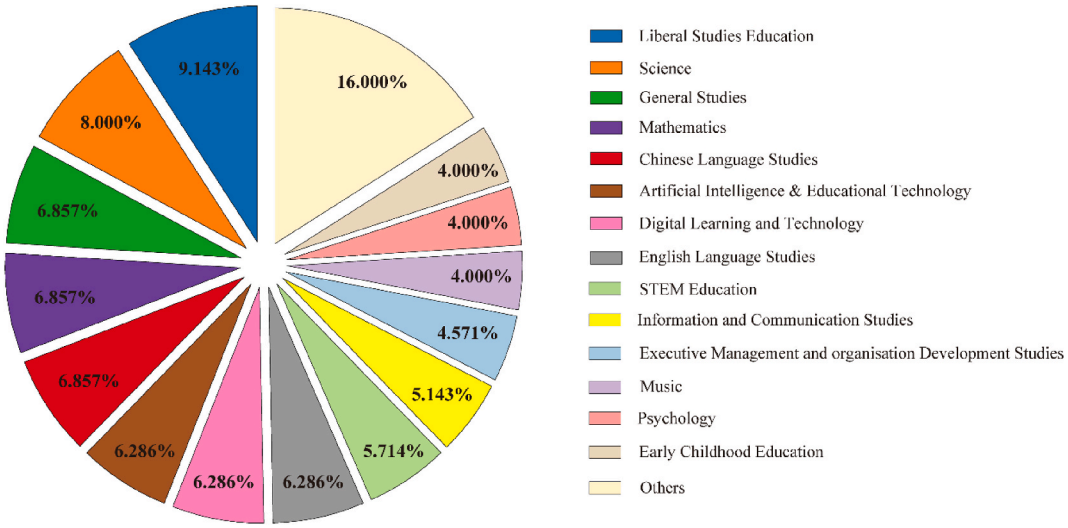


Fig. 1. Distribution of the diverse discipline backgrounds of the university course participants.

together with their teachers.

3.2. Participants

Convenience sampling was used to collect two sets of samples, denoted as Sample 1 and Sample 2, at different phases of this AI literacy programme. A cross-validation method employing different datasets is suggested for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Brown, 2015; Vandenberg & Lance, 2000). Sample 1 (N = 477) was used for scale development, while sample 2 (N = 409) was used for model validation and confirmation. In sample 1, there were 255 (53.459%) females and 219 males (45.912%) (with three participants (.629%) not disclosing their gender). In Sample 2 (N = 409), 212 (51.834%) participants were female, and 197 (48.166%) were male. A total of 370 participants completed the EUAIPS before and after the course.

Growing attention is being given to sample diversity in research, especially psychological research, to better reflect the human phenotype and predict more universal, complete, and precise psychological results (Gurven, 2018; Nielsen et al., 2017). Not only are senior secondary students required to utilise AI efficiently, effectively, and ethically, but AI education should be available to all university students in all disciplines, supporting them to enter a profoundly changed workplace (Hornberger et al., 2023; Wang & Lester, 2023). To help the new generation embrace AI, the Hong Kong Education Bureau has developed AI modules for K-12 students to enhance their AI literacy (Education Bureau, 2024a). In addition, various universities in Hong Kong are also developing and implementing AI literacy programmes for secondary and university students (Kong et al., 2023; Wang & Lester, 2023).

Of the 370 participants, there are 195 senior secondary students and 175 university students. They are from 16 to 24 years old. 181 senior secondary students were from 26 (81.250%) aided schools, 7 senior secondary students from 4 (12.500%) direct subsidy scheme schools, and another 7 senior secondary students from 2 (6.250%) government schools. No students were from private schools. There are 355 aided schools (76.017%), 58 direct subsidy scheme schools (12.420%), 30 government schools (6.424%), and 24 private schools (5.139%) in Hong Kong, respectively. Government schools are managed by the Education Bureau of Hong Kong directly (Education Bureau, 2024b). Aided schools are managed by their own incorporated management committee or school management committee, with their subventions mostly provided by the government. Direct subsidy scheme schools are also managed by their own incorporated management committee or school management committee. They can charge school fees and receive government subsidies based on the number of eligible students in the school. Private schools are self-financed and managed by their management committees. Therefore, the composition of our secondary school sample closely reflected the general school population in Hong Kong based on funding support, making the study sample representative and the results generalisable in Hong Kong. University students were either enrolled in bachelor's degree or higher diploma programmes across diverse disciplines such as liberal studies education (9.143%), science (8.000%), general studies (6.857%), mathematics (6.857%), and Chinese language studies (6.857) and so on. Fig. 1 shows the distribution of the diverse discipline backgrounds of the university course participants.

3.3. Data collection

Before collecting data, ethical approval was obtained through the authors' affiliated university (Ref. no. A2020-2021-0204 and 2021-2022-0325), and informed consent was obtained from all students. Furthermore, participants were informed that their participation was voluntary and that they could withdraw from the research anytime. The course intervention lasted 2–4 weeks, where participants completed the same EUAIPS scale via Qualtrics during class hours. Before the scale implementation, students were given 10–15 min to complete the 11-item EUAIPS scale, which included demographic information (gender, schools, and disciplines).

3.4. Measure

Initially, the 13-item EUAIPS scale with three dimensions was created by drawing on our proposed conceptual framework of empowerment and discussions with the project team. Given that the self-reported items focused on students' empowerment in using AI for problem-solving, the project team added the phrase 'solve problems with AI' to the items to specify the empowerment scenario. A bilingual version of the EUAIPS scale was designed for international use and to reduce students' cognitive load when responding to the questionnaire. The project team reviewed three iterations of these items to assess their clarity and appropriateness, and a consensus was reached on the equivalence of the Cantonese–English version. Dörnyei and Taguchi (2009) note that all items of the self-reported questionnaires need to be positively worded. Thus, we adopted a 5-point Likert response scale, where students rated each item from 1 (strongly disagree) to 5 (strongly agree).

Two experts in computer science and educational assessment were consulted to determine whether the EUAIPS scale was appropriate in the

Table 1
Descriptive statistics of the EUAIPS scale.

	Sample 1				Sample 2			
Items	M	SD	Skewness	Kurtosis	M	SD	Skewness	Kurtosis
Item 1	4.157	.624	−.593	2.154	4.259	.619	−.485	1.027
Item 2	4.199	.645	−.638	1.769	4.286	.621	−.531	1.018
Item 3	4.266	.640	−.738	2.010	4.337	.605	−.589	1.281
Item 4	4.189	.669	−.619	1.295	4.259	.619	−.610	1.643
Item 5	4.021	.670	−.655	1.719	4.205	.600	−.388	1.324
Item 6	3.694	.837	−.217	−.187	3.944	.750	−.258	−.192
Item 7	3.834	.739	−.354	.356	4.042	.683	−.331	.318
Item 8	3.772	.817	−.484	.333	4.000	.721	−.592	1.031
Item 9	3.813	.776	−.315	.076	4.000	.704	−.339	.245
Item 10	4.021	.641	−.546	1.775	4.137	.619	−.408	1.243
Item 11	4.164	.660	−.674	1.767	4.245	.656	−.837	2.301
Item 12	4.065	.706	−.524	.824	4.166	.694	−.589	.962
Item 13	4.164	.657	−.587	1.470	4.289	.618	−.530	1.062

Notes. M = Mean; SD = Standard deviation.

context of AI and to anticipate potential word issues affecting its psychometric properties. For example, for item 10, we considered 'Being able to solve problems with AI allows me to create things (e.g., apps, tools) that are useful to me' and 'Being able to solve problems with AI allows me to create things (e.g., apps, tools) for fun'. However, one expert advised that because the EUAIPS scale concerns students' AI empowerment for problem-solving in the instructional context, 'for fun' may not be relevant. We replaced 'is useful to me' with 'achieve my goals' as the latter better reflects that empowerment increases intrinsic task motivation (Thomas & Velthouse, 1990). Based on the experts' suggestions, we further refined the scale.

3.5. Data analysis

For answering RQ1, EFA and CFA analyses were conducted on sample 1 and sample 2 to determine the factor structure that supported the structural validity of the EUAIPS scale. Measurement invariance across gender was established, supporting the generalisability of the EUAIPS scale. For answering RQ2, we checked the internal consistency, convergent validity, and discriminant validity of the resulting EUAIPS scale. For answering RQ3, we performed paired-sample t-tests on students' responses to the EUAIPS scale.

None of the participants' responses were discarded because there were no item-level missing data. Nineteen outliers were removed by Mahalanobis' distance rule, leading to final sample numbers of 477 (sample 1) and 409 (sample 2). According to Kline's (2015) guideline, the data were normally distributed, with skewness and kurtosis values of all variables falling between the relevant thresholds (±3 for skewness; ±10 for kurtosis, see section 4.1). Descriptive analysis, internal consistency, and bivariate correlations were examined using SPSS (IBM, version 29.0). All other analyses were conducted using the R statistical computing environment (R Core Team, 2020).

EFA is an item reduction process that aims to find a number of items to represent the constructs we retained (Hinkin, 1998). Sample 1 was used for EFA with oblique rotation (direct oblimin) to determine the dimensionality of the EUAIPS scale with 13 items. The Kaiser–Meyer–Olkin (KMO) test and Bartlett's Test of Sphericity were used to check the assumptions of EFA analysis. Next, we decided on the number of factors to retain according to the parallel analysis (Horn, 1965) and theoretical foundations. CFA analysis was then performed to validate the factor structure constructed in EFA using sample 2.

Maximum likelihood estimation was employed to obtain the EFA and CFA model fits. Evaluating the goodness of model fit is based on multiple of indices that satisfy the following criteria: $\chi^2/df < 3$, comparative fit index (CFI), Tucker–Lewis index (TLI) $\geq .95$; root mean square of the residuals (RMSR), root mean square error of approximation (RMSEA) $\leq .08$, and standardised root mean square residual (SRMR) $\leq .08$ (Hu & Bentler, 1999; Kline, 2015). For the EFA model, items with factor loadings lower than .30 (Costello & Osborne, 2019) were deleted. Cross-loading items were also deleted if the difference between the primary and secondary factor loadings was lower than .20 or if items had a secondary factor loading of .30 or above (Schaefer et al., 2015).

A lower Akaike's information criterion (AIC) is preferred when comparing different CFA models, although there are no unified values for a model AIC (Kline, 2015). If the CFA model fit was inadequate, modification indices (MI) were tested to identify any potential missing parameters or any items that could be deleted to improve the model fit, considering theoretical support simultaneously. The internal consistency validity, convergent validity, and discriminant validity of the EUAIPS scale were assessed by checking Cronbach's alpha (>.07), composite reliability (CR), the average variance extracted (AVE), and the inter-construct correlations (Fornell & Larcker, 1981; Nunnally, 1975).

We further carried out a multi-group CFA (MGCFA) to examine measurement invariance of the EUAIPS scale across gender using sample 2. Following a stepwise procedure with more additional constraints being imposed, we tested configural invariance, metric invariance, scalar invariance, and strict invariance (Vandenberg & Lance, 2000). The changes in the values of CFI and RMSEA were used for nested model comparisons because, unlike the chi-square difference ($\Delta\chi^2$), they are not overly sensitive to a large sample size and model complexity (Chen, 2007). invariance models with ΔCFI <.01 and ΔRMSEA <.015 are favoured (Chen, 2007). Finally, we performed a paired sample *t*-test to examine students' empowerment in using AI for problem-solving.

4. Results and discussion

4.1. Descriptive statistics

Table 1 shows that the skewness (min = −.83; max = −.26) and kurtosis (min = −.19; max = 2.30) of items in sample 1 and sample 2 were within the thresholds of ±3 and ± 10, respectively (Kline, 2015), indicating that the responses were normally distributed. The means of the EUAIPS score for each sample ranged from 3.694 to 4.337, and the standard deviations ranged from .600 to .837. High mean values and a low degree of variability in students' responses indicate a high level of empowerment in using AI for problem-solving.

4.2. EFA results

Data from the 13 items in sample 1 were used for EFA analysis according to Preacher MacCallum's (2003) procedures. The KMO value of .955 demonstrated that the sample was suitable for EFA analysis. Bartlett's test of sphericity reached statistical significance, X^2 (78) = 5867. 85, $p < .001$, suggesting that the properties of the correlation matrix could be subjected to developing a factor analysis.

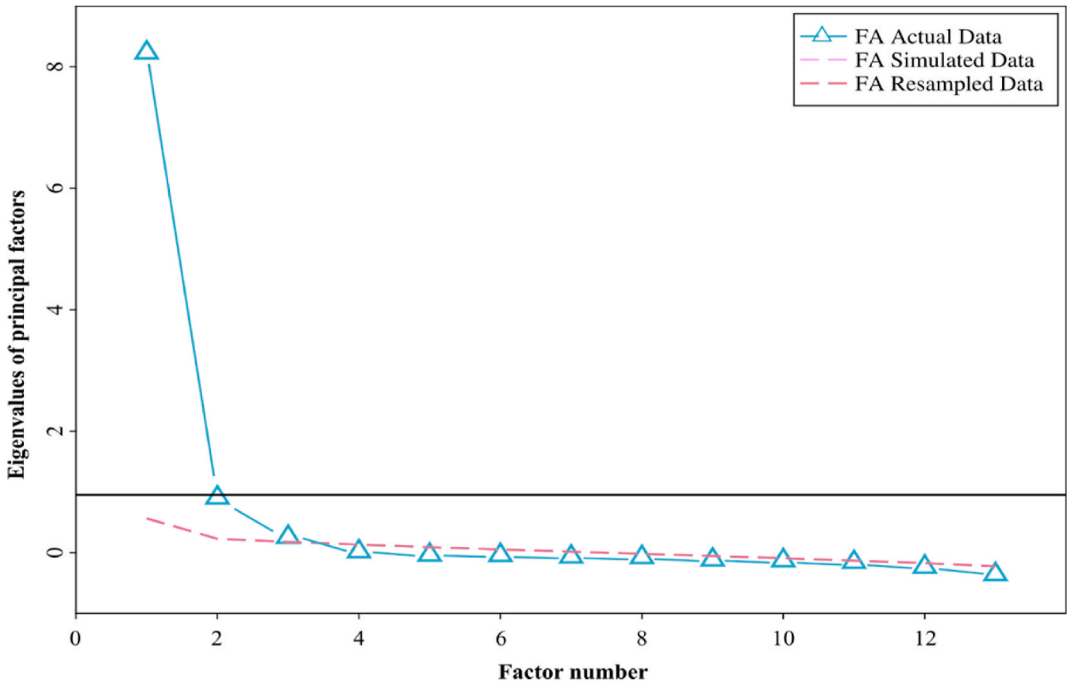


Fig. 2. Parallel analysis scree plot.

Table 2
Factor loadings of the final EFA with direct oblimin rotation and variances of the 12-item EUAIPS scale (N = 477).

Items	Rotated Factor Loading			Community
	Factor 1	Factor 2	Factor 3	
1. I want to apply my AI knowledge and skills to solve problems in daily life.	**.842**	.057	.013	.789
2. I want to solve problems with AI to make people's lives better.	**.939**	.004	−.021	.853
3. I want to solve problems with AI to make daily life easier.	**.911**	−.051	.019	.806
4. I want to apply my AI knowledge and skills to develop interesting solutions to problems.	**.822**	.041	.029	.759
6. I am good at solving problems with AI.	.017	**.920**	−.078	.772
7. I think of myself as someone who can solve problems with AI.	.104	**.752**	.085	.776
8. I have the knowledge and skills to solve problems with AI.	−.057	**.852**	.048	.724
9. I have confidence in my ability to solve problems with AI.	.126	**.514**	.230	.617
10. Using AI to solve problems will help me achieve my goals.	.056	.269	**.613**	.748
11. I want to be good at solving problems with AI.	.232	.028	**.607**	.692
12. Using AI to solve problems is important to me.	−.064	.043	**.925**	.811
13. Using AI to solve problems is useful to me.	.068	−.076	**.891**	.809
Percentage of variance (%)	29.093	23.944	23.250	—
Cumulative of total variance explained (%)	29.093	53.037	76.387	—

Note. EFA = exploratory factor analysis. Factor 1 = Impact of using AI for problem-solving (IP). Factor 2 = Self-efficacy in using AI for problem-solving (SE). Factor 3 = Meaningfulness in using AI for problem-solving (MN). Factor loadings >.50 in boldface. The item in italics was removed from the final confirmatory factor analysis model.

We performed a parallel analysis with 2000 iterations; its result and a visual inspection of scree plot suggested that three factors were the optimal solution (see Fig. 2), aligning with our theoretical framework. Thus, we ran an initial three-factor EFA analysis. An examination of the pattern matrix indicated one cross-loaded item that the factors could not clearly interpret (item 5, 'I can learn to be better at solving problems with AI') because it had a ratio of below .20 between the primary loading (.412) and the highest secondary loading (.314).

Therefore, we reran the EFA after removing this cross-loaded item. The EFA model factor then had a better fit: CFI = .991, TLI = .983, RMSR = .013, RMSEA = .054 (90% CI [.039, .069]). Therefore, this three-factor model of the 12-item EUAIPS scale achieved a simple structure and was chosen as the best model (see Table 2). Factor 1 (IP, 4 items), Factor 2 (SE, 4 items), and Factor 3 (MN, 3 items) explained 29.093%, 23.944%, and 23.250% of variance after rotation, respectively. Together, these three factors explained 76.287% of the variance in the EUAIPS scale.

4.3. CFA results

Sample 2 was used as a CFA set to validate the three-factor structure of the EUAIPS scale established in EFA (see Table 3). The fit indices of the EUAIPS scale's three-factor model fit (Model 1) were satisfactory except for the values of χ^2/df (3.961) and RMSEA (.085; 90% CI [.073, .098]). Thus, we decided to test the MI to identify the problematic items that caused the poor data fit. The MI results showed that the correlated errors between item 10 and item 13 yielded the largest MI (MI = 43.069), suggesting these two items had some common variance that was not explained by the dimension of MN. Furthermore, item 13 had other correlated errors with items from a pair in the same subscales. If correlated errors exist, one item in a correlated pair can be deleted to enhance the model fit (Muthén & Muthén, 2012). Theoretically, item 13 describes the usefulness of using AI for problem-solving generally; therefore, it possibly overlaps with the dimensions of perceived impact/competence manifested in empowerment (Spreitzer, 1995). Thus, we decided to delete item 13.

When this change was carried out, the respecified CFA model of the EUAIPS scale achieved a more satisfactory fit with lower AIC values:

Table 3
Fit indices of CFA models of the EUAIPS scale.

Models	χ^2	df	χ^2/df	CFI	TLI	RMSEA (90% CI)	SRMR	AIC
Three-factor CFA model	202.001***	51	3.961	.966	.956	.085 (.073, .098)	.033	5548.895
Revised three-factor model	106.091***	41	2.588	.983	.978	.062 (.048, .077)	.026	5213.273
One-factor model	714.001***	44	16.227	.830	.788	.193 (.181, .206)	.074	5815.182

Note. CFI = Comparative fit index; TLI = Tucker–Lewis index; RMSEA = Root mean squared error of approximation; SRMR = Standardised root mean squared residual; AIC = Akaike information criterion; CFA = Confirmatory factor analysis. ***$p < .001$.

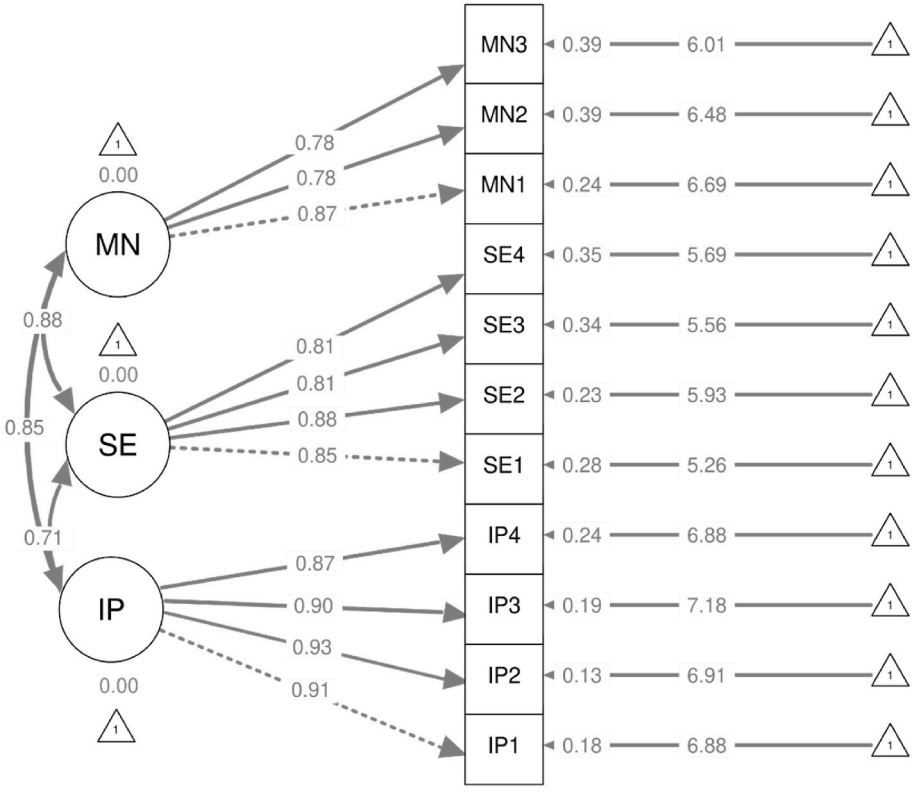


Fig. 3. The three-factor CFA model of the EUAIPS scale.
Note. CFA = Confirmatory factor analysis. IP1–IP4 = Impact of using AI for problem-solving (item 1, item 2, item 3, and item 4). SE1−SE4 = Self-efficacy in using AI for problem-solving (item 6, item 7, item 8, and item 9). MN1–MN4 = Meaningfulness in using AI for problem-solving (item 10, item 11, and item 12).

Table 4
Standardised factor loadings of the final CFA model of the EUAIPS scale (N = 409).

Construct	Items	Standardised factor loadings (λ)	AVE	CR	Cronbach's α
IP	Item 1	.906	.789	.937	.946
	Item 2	.933			
	Item 3	.901			
	Item 4	.870			
SE	Item 6	.851	.700	.903	.902
	Item 7	.875			
	Item 8	.810			
	Item 9	.809			
MN	Item 10	.871			
	Item 11	.783			
	Item 12	.780	.709	.879	.852

Note. CFA = Confirmatory factor analysis; AVE = Average variance extracted; CR = Composite reliability; IP = Impact of using AI for problem-solving; SE = Self-efficacy in using AI for problem-solving; MN = Meaningfulness in using AI for problem-solving.

$\chi^2(41) = 106.091$, $p < .001$, χ^2/df = 2.60, CFI = .983, TLI = .978, RMSEA = .062 (90% CI [.048, .077]), SRMR = .026, AIC = 5213.273. All the standardised factor loadings were statistically significant, as illustrated in Fig. 3 and Table 4. The EUAIPS data was collected only through self-reported questionnaires, so we also examined CMV using Harman's one-factor test (Podsakoff et al., 2003). The results demonstrated that no single factor appeared, but the general factor captured 65.901% of the variance in 9 indicators. Therefore, CMV may be an issue in this study. It is common when CMV appears in research findings because we hardly completely exclude its effect because procedural or statistical remedies cannot be applied in all cases (Tehseen et al., 2017).

Aiding from the correlations among these three factors above .70, the revised three-factor model had a significantly better fit than the one-factor model of the EUAIPS scale: $\Delta\chi2(3) = 607.910$, $p < .001$. These results supported the convergent validity of the three-factor EUAIPS scale, reflecting a lower probability of CMV inflating or deflating the relationship between constructs (Podsakoff & Organ, 1986). Hence, the CFA results supported the three-factor model of the EUAIPS scale, which was used for all subsequent analyses. Therefore, the finalised scale consisted of 11 items with three factors.

Table 5
Inter-correlation results.

Construct	IP	SE	MN
IP	**.889**		
SE	.660***	**.837**	
MN	.769***	.762***	**.842**

Note. Correlations are below the diagonal, and all squared roots of average variance extracted values are displayed on the diagonal. IP = Impact of using AI for problem-solving; SE = Self-efficacy in using AI for problem-solving; MN = Meaningfulness in using AI for problem-solving. ***$p < .001$.

4.4. Internal consistency, convergent validity, and discriminant validity

Table 4 shows that the three subscales of the EUAIPS scale showed good internal consistency/reliability, with the following Cronbach's alpha values: .946 for IP, .902 for SE, and .852 for MN. All the values were higher than the threshold of .70 (Kline, 2015). All standardised loadings exceeded .5 (Hair et al., 1995). The AVE for each construct ranged from .700 to .789, and the CR for these three constructs exceeded the threshold of .70. Hence, the convergent validity of the EUAIPS scale was supported. The EUAIPS scale met the criteria for discriminant validity, as the square roots of the AVE of each construct all exceeded the inter-construct correlations, following the Fornell and Larcker (1981) criterion (see Table 5).

4.5. Measurement invariance results

Without establishing measurement invariance, a comparison of the constructs' scores in different groups can be misleading because we do not know whether we compare apples with oranges (Hoyle & Smith, 1994). Table 6 shows that the configural invariance model, which served as the baseline model, had a satisfactory fit: (CFI = .980, TLI = .973, RMSEA = .069 [90% CI (.053, .085)], SRMR = .031). This refers to the invariance of factorial structure across groups without imposing constraints on all parameters. We then tested the metric invariance model, where factor loadings were constrained to be equal in the male and female groups. The differences between metric and configural invariance were ΔCFI = −.001 and ΔRMSEA = −.003, supporting metric invariance. Scalar invariance model was created by imposing the equality of factor loadings and intercepts. The fit results of scalar invariance were good: ΔCFI = .002 and ΔRMSEA = −.004. The last more restrictive strict invariance model, which constrained the equality of factor loadings, intercepts, and residual invariance between gender groups, was then inspected. Strict invariance was not supported because ΔCFI = −.021 and ΔRMSEA = .022. Thus, scalar invariance across gender was established, indicating that comparison of the mean EUAIPS scores across genders is meaningful.

4.6. Developing empowerment for problem-solving with AI

From Table 7, the results demonstrated that the course resulted in significant improvements in senior secondary and university students' perceptions of the impact of using AI for problem-solving [t (369) = −3.688, $p < .001$] and self-efficacy in the application of AI for solving real-life problems [t (369) = −7.245, $p < .001$]. In addition, students perceived using AI for problem-solving to be more meaningful [t (369) = −3.363, $p < .001$]. The means for all specific items had a significant enhancement except for item 11 (#I want to be good at solving problems with AI), possibly because the course did not provide a level of training in AI applications enabling the students to reach proficiency (Luckin et al., 2022)

4.7. Implication and contribution of the study

Theoretically, the three distinct factors of the 11-item EUAIPS scale, along with their high correlations, support the argument that empowerment is a multifaceted construct at the individual level with impact, self-efficacy, and meaningfulness as core components, while three of them maintain sufficient differentiation to be regarded as unique constructs (Frymier et al., 1996; Perkins & Zimmerman, 1995; Scheel & Rieckmann, 1998; Thomas & Velthouse, 1990). Such a finding echoes the theory of planned behaviour, signifying that perceived behavioural control (empowerment) is central in promoting students' use of AI for problem-solving and operates well in student-centred classrooms to augment students' intrinsic motivation to complete tasks (Ajzen, 1985; Kong et al., 2024; Larson et al., 2016). Secondly, the three-factor model of the EUAIPS scale provides empirical evidence for prior studies related to AI literacy, emphasising the affective dimension and psychological mechanism essential for students' long-term use of AI (Carolus et al., 2023; Kong et al., 2024; Ng et al., 2024). In addition, the good psychometric properties of the EUAIPS scale reflect that AI users need to be equipped with affective capabilities to understand and solve problems in real-life scenarios, in addition to engaging the cognitive and social process of problem-solving in human-AI collaboration (Joksimovic et al., 2022).

From the practical perspective, this study provides a reliable and robust instrument for researchers and practitioners to measure students' empowerment in using AI for problem-solving and capture the impact of interventions to improve it. With pre- and post-intervention measurement, the scale effectively captures students' positive changes in three aspects for students' empowerment in using AI for problem-solving. This promising finding implies that educators can apply this measure to gain deeper insights into how students' empowerment in using AI for problem-solving contributes to their AI literacy skills, analyse what tasks or environments to foster specific aspects of psychological readiness for using AI, and develop effective strategies to enhance its growth (Conger & Kanungo, 1988; Long & Magerko, 2020; Luechauer & Shulman, 1993; Thomas & Velthouse, 1990). Curriculum designers of AI literacy programmes can align subjects with the dimensions of the EUAIPS scale, crafting tasks that empower individuals to perform and exercise control, fostering a proactive readiness in the new generation of educated citizens, regardless of AI programming background, to navigate an AI-saturated world with AI literacy skills.

The PBL approach implemented in this study was applied to inspire students to use AI tools for yielding problem-solving products, effectively scaffolding students' AI learning process and enhancing their capability to apply AI (Lu & Fan, 2023; Vargas et al., 2020). Firstly, the PBL approach allowed students not only to experience leveraging AI assistance in their group projects but also to participate in the presentations of their learning peers. These presentations enabled students

Table 6
Measurement invariance results across gender.

Models	x^2	df	x^2/df	CFI	TLI	RMSEA (90% CI)	SRMR	ΔCFI	ΔRMSEA
M1	162.189***	82	1.978	.980	.973	.069 (.053, .085)	.031	—	—
M2	171.138***	90	1.902	.979	.975	.066 (.051, .081)	.042	−.001	−.003
M3	174.139***	98	1.777	.981	.978	.062 (.046, .076)	.042	.002	−.004
M4	266.568***	109	2.446	.960	.960	.084 (.071, .097)	.043	−.021	.022

Note. CFI = Comparative fit index; TLI = Tucker–Lewis index; RMSEA = Root mean squared error of approximation; SRMR = Standardised root mean squared residual. M1 = Configural invariance; M2 = Metric invariance; M3 = Scalar invariance; M4 = Strict invariance.

Table 7
Paired-sample t-tests of senior secondary and university *students' responses to the EUAIPS* (N = 370).

Constructs	Before course		After course				
	M	SD	M	SD	M_{diff}	df	t
IP	4.211	.581	4.305	.573	−.094	369	−3.688***
1. I want to apply my AI knowledge and skills to solve problems in daily life.	4.170	.603	4.284	.614	−.114	369	−3.841***
2. I want to solve problems with AI to make people's lives better.	4.211	.637	4.303	.625	−.092	369	−3.141**
3. I want to solve problems with AI to make daily life easier.	4.276	.633	4.360	.601	−.084	369	−2.754**
4. I want to apply my AI knowledge and skills to develop interesting solutions to problems.	4.187	.663	4.273	.623	−.086	369	−2.652**
SE	3.783	.676	4.002	.632	−.219	369	−7.245***
6. I am good at solving problems with AI.	3.689	.828	3.943	.740	−.254	369	−6.058***
7. I think of myself as someone who can solve problems with AI.	3.849	.713	4.041	.684	−.192	369	−5.152***
8. I have the knowledge and skills to solve problems with AI.	3.773	.805	4.027	.709	−.254	369	−6.109***
9. I have confidence in my ability to solve problems with AI.	3.822	.748	3.997	.700	−.175	369	−4.871***
MN	4.098	.593	4.187	.574	−.089	369	−3.363***
10. Using AI to solve problems will help me achieve my goals.	4.027	.628	4.135	.619	−.108	369	−3.380***
11. I want to be good at solving problems with AI.	4.197	.647	4.257	.639	−.059	369	−1.733
12. Using AI to solve problems is important to me.	4.070	.695	4.170	.691	−.100	369	−2.823**

Note. M = Mean; SD = Standard deviation; M_{diff} = Mean difference; IP = Impact of using AI for problem-solving; SE = Self-efficacy in using AI for problem-solving; MN = Meaningfulness in using AI for problem-solving. *$p < .05$; **$p < .01$; ***$p < .001$.

to share the successful experiences of their counterparts in using AI tools to tackle various problems that they considered meaningful (Blumenfeld et al., 1991). This, in turn, enhanced the probability that the students would recognise the impact of using AI to address societal issues. Furthermore, students are tasked with applying their AI concepts to solve problems with minimal support from their teachers through the PBL approach. This problem-solving process enables students to feel more proficient in utilising AI in their learning and daily lives. Owing to embracing the PBL learning approach, students are required to work together in groups to formulate problems. This process of collaborative problem formulation enables students to recognise the significance of utilising AI for problem-solving, empowering them to identify problems they personally deem meaningful in both their learning and daily lives.

In summary, this study serves to inform AI literacy curriculum designers of the need to put the psychological construct of empowering students in using AI concepts for problem-solving into practice in their AI literacy curriculum by using AI for developing products for solving real-life problems (Chiu et al., 2022; Dai et al., 2020; Saengrith et al., 2022). These activities should enable students to recognise the impact of AI on society, realise their self-efficacy in using AI concepts for problem-solving, and understand more thoroughly the meaningfulness of harnessing AI.

5. Conclusions, limitations, and future research directions

This study provided a valid instrument for researchers and practitioners to measure students' empowerment in using AI for problem-solving, contributing to current AI-related research (e.g., AI literacy) and adding novel applications for conventional psychological constructs in the AI context (Chiu et al., 2022; Kong et al., 2024; Ng et al., 2024; Wang, King, et al., 2023). The EUAIPS scale also attempts to fill a gap by incorporating empowerment into addressing students' psychological and affective needs when using AI technology and solving problems (Carolus et al., 2023; Kong et al., 2024). This suggests that empowerment is pivotal in stimulating students' interest in and motivation for using AI for problem-solving in educational or other organisational environments.

Despite the promising results, there are three limitations of this study. Firstly, this study mainly relied on self-reported questionnaires with a common method bias of over 60% (Podsakoff et al., 2003; Tehseen et al., 2017). Future studies should use qualitative approaches and mixed methods (e.g., focus groups, class observation, and reflective diaries) to triangulate the accuracy of self-reports, further improving the theoretical contributions and understanding of the EUAIPS scale. Secondly, although this study included a diverse sample across school types and university disciplines and might have other implications for similar educational contexts, it mainly relies on Hong Kong participants. In terms of cultural values, Hong Kong students are situated in a Confucian Heritage Culture (CHC) characterised by collectivism that emphasises interdependence, higher power distance, and analytic mode of thought, while students in Anglo-Saxon context are featured by individualist values that underline independence, individual initiative, low power distance, and intuitive approaches (Carless, 2012; Ho, 2020; Sigler & Pearson, 2000). On the other hand, there are some cross-cultural disparities in AI development, application, ethics, and governance across regions (e.g., Europe, North America, and East Asia, particularly regarding critical issues like data privacy.

These cross-cultural values and contextual differences largely influence students' perceptions of empowerment in varied educational contexts, for instance, how they believe that their problem-solving through using AI impact their learning or learning or life, what competence is necessary to complete the project, and what problems they solve are meaningful. Students across different regions have varying perceptions

of empowerment, which, in turn, influence their behaviour in using AI for problem-solving and the quality of their project outcomes (Ajzen, 1985; Sigler & Pearson), including teamwork, decision-making, and problem-solving during the process of leveraging AI power. Therefore, Future research should examine whether the findings of the EUAIPS scale can be replicated in other sociocultural environments to advance its international application. Additionally, the current study focused on developing and validating the EUAIPS scale without exploring its predictive role. An interesting direction for future studies would be to investigate the causal relationships between the EUAIPS scale and learning-related variables, such as the understanding of AI concepts and the ability to use AI concepts for problem-solving.

CRediT authorship contribution statement

Siu Cheung Kong: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Jinyu Zhu:** Writing – original draft, Methodology, Investigation, Formal analysis. **Yin Nicole Yang:** Writing – review & editing, Validation, Methodology, Investigation.

Ethical approval

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 all participants, and their privacy rights were strictly observed. The data can be obtained by sending request e-mails to the corresponding author.

Declaration of competing interest

The authors declare that there is no potential conflict of interest in this study that could have appeared to influence the work reported in this article.

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