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Developing and validating an artificial intelligence identity scale for artificial intelligence literacy development

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Abstract

The development of artificial intelligence (AI) literacy in students is a well-recognised educational goal. AI literacy consists of not only technical knowledge of AI but also the psychological readiness to proactively use AI in daily life. The concept of identity in psychology is known to have a significant influence on students' behavioural readiness and tendency. Building on the theories of personal and social identities, situated learning and collaborative learning, we have conceptualised AI identity and developed and validated an AI Identity Scale in this study. We conducted confirmatory factor analysis on 222 survey responses, and uncovered four subscales, namely AI engagement, AI affiliation, AI actualisation, and AI goal setting. We also compared students' level of AI identity before and after participating in a problem-solving project-based AI literacy course. Significant enhancement was observed in their overall AI identity and in the AI engagement, AI affiliation, and AI goal setting subscales. The AI Identity Scale could be a valuable resource in measuring students' psychological readiness to use AI. Future studies may model the relationship of AI identity with other dimensions of AI literacy.

Keywords: Artificial intelligence identity, Artificial intelligence literacy, Collaborative learning, Problem-solving, Situated learning

Introduction

The significant influence of artificial intelligence (AI) on how society functions is widely recognised (European Commission & European Education and Culture Executive Agency, 2023; United Nations High-Level Advisory Body on Artificial Intelligence, 2023; White House, 2023). To prepare students for surviving and participating in the future world where AI plays a central role, there is consensus in the education community for developing students' AI literacy (Kong et al., 2024; Laupichler et al., 2022; Ng et al., 2024). In recent years, it is increasingly agreed that AI literacy consists of not merely the technical knowledge or skills to proactively interact with AI, including solving problems using AI, but also the psychological readiness to do so (Dai et al., 2020; Kong et al., 2024; Wang et al., 2023). Previous research in the emotional or psychological dimension of AI literacy has largely focused on students' confidence, empowerment, and their perception of AI's value and relevance (Dai et al., 2020; Kong et al., 2022; Lu & Lin, 2025; Ng et al., 2024). However, in psychology, the effect of individuals' identity on their behavioural tendency and readiness to engage in certain behaviours is well-understood (Alfrey et al., 2023; Oyserman, 2009; Verplanken & Sui, 2019). Indeed, the concept of identity has been extensively adopted in educational fields closely related to AI literacy, including science, technology, engineering, and mathematics (STEM) (Dou et al., 2019; Kim et al., 2018), computational thinking (Kong & Wang, 2020; Tissenbaum et al., 2019), and information technology (IT) (Carter & Grover, 2015; Mosafer & Sarabadani, 2021). When viewed in the context of AI literacy development, it is necessary to investigate students' level of AI identity as a part of their complete psychological readiness to use AI in their daily lives.

Background of Study

Identity in Psychology and Education

In psychology, the concept of identity can in general be dichotomised into personal identity and social identity (Alfrey et al., 2023; Ellemers et al., 2002). Personal identity usually refers to the set of beliefs and values to which we feel attached (Crocetti et al., 2023; Olson, 2023; Schwartz et al., 2014). As individuals integrate their experiences with matters meaningful to them, they develop their own personal identity distinct from others' personal identities (Erikson, 1968; Jenkins, 2008). Thus, the study of personal identity frequently centres on individuals' continued development of their personal identity (Crocetti et al., 2023), particularly in adolescence (Branje et al., 2021; Pfeifer & Berkman, 2018), and is sometimes regarded a subfield of developmental psychology (Schwartz et al., 2012).

Social identity, on the contrary, concentrates on individuals' relationship with others, especially the social groups of which they perceive themselves as a member and the consequences of this perception (Jenkins, 2008). The social identity theory posited that individuals' sense of belonging to a social group motivates them to engage in behaviours in relation to other social groups (Tajfel and Turner, 1979). The self-categorisation theory and hypothesises that as individuals self-categorise themselves into a social group, they increasingly view themselves as equivalent to fellow members of that group (Turner et al., 1987). As such, individuals' social identity not only concerns why they perceive themselves as a member of a group, but also determines their feelings, attitudes, and behaviours (Hornsey, 2008).

There is consensus in the education community that developing students' identity is one of the objectives of education and learning (Kaplan & Flum, 2012). Importantly, researchers have reported and discussed the effects of education on both personal and social identities. Sfard and Prusak (2005), for instance, suggested education is the conduit through which students close the gap between their present and future personal identities (or, in the words of Sfard and Prusak, actual and designated identities). Lave and Wenger (1991), on the other hand, maintained that learning is a collective process which not merely takes place in individuals' mind, and that as students participate in a learning community, they form and reinforce their membership of that community. It is worth noting that personal and social identities are not as independent to each other as they might seem. Indeed, peers' influence on high school students' own career goals is well-documented, leading to recommendations that teachers leverage students' social interactions and collaborations to help them explore their personal careers and purposes (Yeager et al., 2017).

Social Identity, Situated Learning and Collaborative Learning

First proposed by Lave and Wenger (1991), the situated learning theory (SLT) closely aligns with social identity. It consists of three core ideas: (1) contexts in which students learn are instrumental to their learning (Bell et al., 2013); (2) students learn when they engage in authentic practices to actualise their goals (Orgill, 2007); and (3) students develop senses of affiliation to a community and identity through participating in practices representative of that community (Handley et al., 2006).

Though not explicitly stated in the initial conception of SLT, collaborative learning is generally regarded and recommended as an element of situated learning (Herrington & Oliver, 2000; Pérez-Sanagustín et al., 2015). Indeed, both SLT and collaborative learning (sometimes termed cooperative learning) heavily stress students' social interactions and help develop students' social identity (Adams et al., 2011; De Corte, 2017; Dyson et al., 2004). By collaboratively participating in learning activities with peers, students increasingly feel their peers and themselves belong to the same community. This forms a positive feedback loop, where students' collaboration with peers helps them build their social identity, and their social identity encourages them to further engage with and behave like their peers (Mavri et al., 2021; Rushton et al., 2025; Taconis & Bekker, 2023).

Artificial Intelligence Identity

Artificial intelligence (AI) identity is conceptualised based on the relationship between social identity, situated learning, and collaborative learning, as well as the contribution of personal identity, which as discussed above is not entirely independent from social identity to the development of individuals' holistic identity. As reviewed above, students' active engagement or participation in authentic learning activities is instrumental in forming in the first place their social identity as someone belonging to a certain community. Engagement is also crucial in continuously moulding students' personal identity since formation, as active participation also helps them explore what their social identity entails in terms of their beliefs and values (Branje et al., 2021; Karaś et al., 2018). Often accompanying active engagement is peer collaboration, which has been shown to promote students' feeling of affiliation to fellow social group members and their sense of belonging and attachment to the social group. These feelings, in turn, help shape their social identity (Handley et al., 2006) and, hence, their behaviours and attitudes (Hogg & Smith, 2007; Rathbone et al., 2023).

Although SLT and collaborative learning place more emphasis on the learning process over the product, students' successful actualisation of their goals during the learning process is arguably equally critical in their AI identity development. Indeed, it has been reported that individuals realising and accomplishing their personal goals, even seemingly insignificant ones, can influence their personal identity, which affects their perception of personally meaningful matters and their future goals, including those related to their careers (Christiansen, 2000). Lastly, the relationship between individuals' identity and their career choices, particularly in STEM, has been extensively documented (Hazari, et al., 2010; Myint & Robnett, 2024). The tendency to have a future career related to AI may be regarded as an extension of the actualisation of personal goals using AI, since individuals collaborate with fellow self-identified members of the AI community to set goals and work towards achieving them using AI. This also aligns with the notion of designated (or future) identity that Sfard and Prusak (2005) proposed, the development of which they recommended be the goal of education. Figure 1 illustrates the constituent dimensions of AI identity and their relationship with each other.

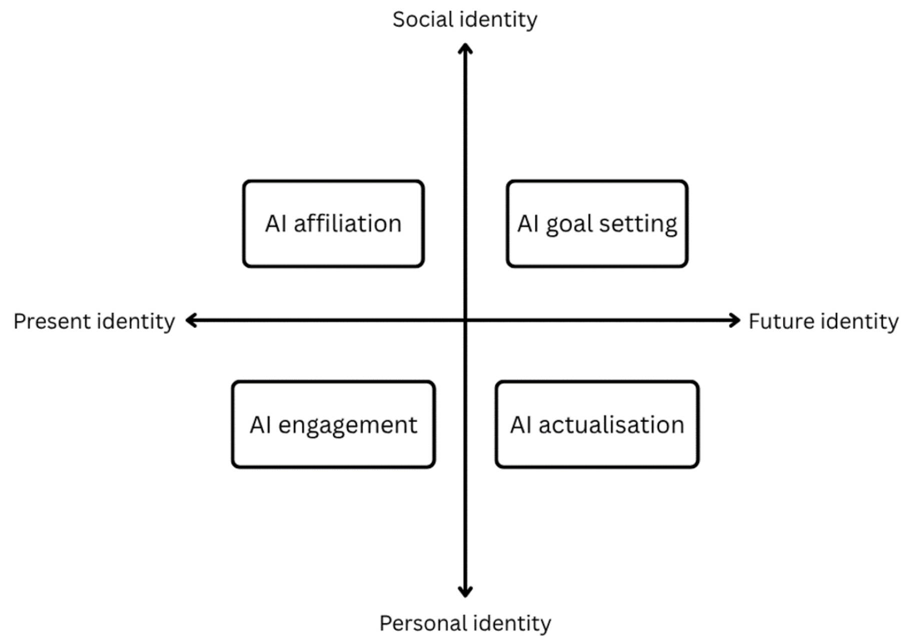

Fig. 1 Constituent dimensions of AI identity and their relationship with each other

Having conceptualised what constitutes AI identity, it is important to distinguish AI identity and other similar psychological constructs. In the field of AI literacy, recent years have seen AI empowerment receiving extensive attention (Dai et al., 2020; Kong et al., 2022; Lu & Lin, 2025; Ng et al., 2024). AI empowerment, which encompasses students' self-efficacy in using AI and the perceived meaningfulness and impact of AI usage, is a central factor in students' psychological readiness to apply AI in their lives (Kong et al., 2021). However, AI empowerment chiefly concerns whether students feel they are capable of applying AI, whereas AI identity is related to students' perception of their position with respect to peers and the larger AI community.

AI identity is also distinct from and complements the study of identity in other STEM-related disciplines. While AI identity encompasses four dimensions along the social/personal identity spectrum and the present/future identity spectrum (see Figure 1), IT identity largely focuses on individuals' perception of the importance of using IT to their sense of self (Carter & Grover, 2015; Mosafer & Sarabadani, 2021), which is similar to the AI actualisation dimension in our conceptualisation of AI identity. STEM identity, on the other hand, emphasises individuals' sense of affiliation to the STEM community and their career orientation (Dou et al., 2019; Kim et al., 2018), which in line with the AI affiliation and AI goal setting dimensions of AI identity. Compared to these similar constructs in other STEM-related disciplines, AI identity more comprehensively captures students' identity formation and development as AI users. The focus of AI identity on using and applying AI, as opposed to concentrating on the development of AI, is also more relevant to students' daily lives.

With the unique construct of AI identity defined, we developed and validated an instrument to measure students' AI identity after a project-based AI literacy course, namely the AI Identity Scale. The following research questions were addressed: (1) To what extent is the AI Identity Scale valid? (2) How did the AI identity of senior secondary and university students change after the AI literacy course?

Methodology

AI Identity Scale

The AI Identity Scale was designed to measure students' AI identity after participating in a project-based AI literacy course. The development process of this instrument involved a collaborative effort by a team of educators who possessed extensive knowledge and experience with the course curriculum. They first reviewed key or recent psychology and education literature on identity formation, focusing on close related constructs such as STEM identity and computational identity (e.g., Kaplan & Flum, 2012; Bae & Lai, 2020; Kim et al., 2018; Kong & Wang, 2020; Rogers, 2018; Simpson & Bouhafa, 2022; Starr et al., 2020). An initial set of items was then generated for the AI Identity Scale, which were then revised. The iterative process of item generation and revision continued until a unanimous consensus was reached within the team. All items of the AI Identity Scale consisted of single statements to which students responded by selecting from a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*) (Likert, 1932). There were no negatively worded statements. The Cronbach's alpha statistic was used to measure the reliability of the AI Identity Scale, indicating the degree to which all the items in the scale measured the same construct. A higher Cronbach's alpha indicates a more internally consistent and a more reliable instrument (Cronbach, 1951). The Cronbach's alpha reliability of the whole scale was .956. The full instrument is presented in Appendix 1.

Course Implementation and Design

As this study is an extension of a previous evaluation of an AI literacy course (Kong et al., 2024), the implementation and design of the course under study adhered to that of the course studied in Kong et al. (2024). The course was administered in a university in Hong Kong as part of an AI literacy programme, which, in turn, was part of a project to promote AI literacy in university and senior secondary students. Offered to university and senior secondary students at no cost and without course credits, the project-based, student-centred course made up of workshops that totalled to 14 learning hours. The beginning of the course saw the students being introduced to ethical principles and issues pertaining to the application of AI, specifically the need to respect for human autonomy, AI models having a fair distribution of harms and gains to society, and the gains of AI models outweighing their harms. Afterwards, the students engaged in a group project where they solved problems with readily available AI-powered platforms, beginning by identifying a problem these platforms could solve. Next, the instructors demonstrated how to use some of these platforms. Examples included Microsoft Azure Question Answering, Google Teachable Machine, and Microsoft Azure Custom Vision, which were respectively used for creating chatbots, classifying images and sound, and detecting objects from images. Individual project consultation for each group was also provided. Guidance from the instructors placed heavy emphasis on the five steps of machine learning (namely, problem definition, data collection, data pre-processing, model training, and inference and prediction), which served as a guiding framework for the students in designing their AI solutions. The instructors also helped the students contemplate the ethical implications of their AI solutions and potential mitigation strategies. The students then worked closely in groups on collaborative project work to develop AI solutions to problems they identified using the AI-powered platforms. This process included gathering data, training AI models, as well as deliberating on possible enhancements of the proposed solutions, the obstacles they encountered, and the ethical ramifications of the solutions and of the AI problem-solving process. At the end of the course, the students orally presented their solutions and the associated ethical considerations. Each group also peer-evaluated and provided constructive feedback to other groups' solutions and reflections. Representative project titles are listed in Table 1.

Table 1 Representative project titles

Project titles
Bilingual first-aid chatbot
Traffic accident recognition notification system
Child outdoor safety alert system
Musical instrument recognition from sound
Chatbot for understanding implicit meaning in speech
Predicting housing prices in Singapore
Identifying portrait subjects looking into the camera or not
Chatbot for early detection of emotional distress
Helping kindergarteners recognise coins

Course Participants

As with the course reported in Kong et al. (2024), students from secondary schools in Hong Kong and from the university where the course was implemented were openly recruited and participated voluntarily with freedom to withdraw at any stage. It was the third and last module of the AI literacy programme of which the course under study was a part, with the preceding two modules comprising 18-hour courses that introduced the conceptual underpinnings of machine learning and deep learning and a framework for problem-solving with AI known as the five steps of machine learning (Kong et al., 2022). All participating students gave informed consent. The institutional Human Research Ethics Committee has granted ethical approval for data collection (Ref. no. A2020-2021-0204 and 2021-2022-0325). The demographics of the students are detailed in Table 2.

Table 2 Distribution of students by level of study, gender, and knowledge in programming

Level of study	
University	79 (35.6%)
Senior secondary	143 (64.4%)
Total	**222 (100%)**
Gender	
Female	98 (44.1%)
Male	124 (55.9%)
Total	**222 (100%)**
Programming knowledge	
Know programming	111 (50.0%)
Do not know programming	111 (50.0%)
Total	**222 (100%)**

Confirmatory Factor Analysis

To validate the hypothesised four-construct model of AI identity, second-order confirmatory factor analysis (CFA) was conducted with SPSS Amos 28 using the maximum likelihood estimation method. Students' post-course response to the scale items was used as observed variables.

Before performing CFA, the skewness and kurtosis of the observed variables were examined. A perfectly normally distributed dataset has kurtosis and skewness of zero, and the closer to zero the kurtosis and skewness of an observed dataset, the closer to perfectly normally distributed it is (Cain et al., 2017). Table 3 shows the skewness and kurtosis of all items of the AI Identity Scale, which were all within ±1, meaning it is suitable for CFA with maximum likelihood estimation.

Table 3 *Skewness and kurtosis of AI Identity Scale items*

Item	Skewness	Kurtosis
Eng1	-0.29	-0.65
Eng2	-0.37	-0.67
Eng3	-0.26	-0.64
Eng4	-0.38	-0.51
Aff1	-0.47	0.19
Aff2	-0.16	-0.75
Aff3	-0.32	-0.53
Act1	-0.27	-0.69
Act2	-0.31	-0.68
Act3	-0.22	-0.61
Act4	-0.29	-0.66
Goal1	-0.40	-0.41
Goal2	-0.20	-0.88
Goal3	-0.39	-0.40

Results and Discussion

Confirmatory Factor Analysis

Goodness of CFA model fit was assessed using the comparative fit index (CFI), the Tucker-Lewis index (TLI), the standardized root means squared residual (SRMR), the root mean square error of approximation (RMSEA), and the chi-squared ($\chi 2$) statistic. Brown (2015) stated that a CFI $\geq .95$ and a TLI $\geq .95$ are required for a well-fit model, while Hu and Bentler (1999) additionally suggested an SRMR $\leq .08$ as an indicator of good model fit. An RMSEA $\leq .08$ is also needed to accept a CFA model (Browne & Cudeck, 1992). Lastly, although the result of $\chi 2$ test of a well-fit model should be statistically insignificant (i.e. p $\geq .05$), the significance of the test is sensitive to sample size, where a large sample easily leads to statistically significance and a false rejection of an otherwise well-fit model (Bentler & Bonett, 1980). All fit indices showed the four-construct CFA model of AI identity was well fit: $\chi 2$ (73) = 140.954, $p < .001$, CFI = .974, TLI = .968, SRMR = .035, RMSEA = .065. Table 4 lists the mean, standard deviation, Cronbach's α reliability, and factor loading of the entire AI Identity Scale, each of the four subscales, and each scale item. Also, as shown in Table 5, no item pairs have modification indices over 15, which is the typical threshold for indicating correlation among items (Aluja et al., 2005). Figure 1 depicts the factor structure of the AI identity model with standardised coefficients.

Table 4 Mean, standard deviation, Cronbach's α reliability, and factor loading of the AI Identity Scale, subscales, and survey items

Scale/subscale/item	Cronbach's α reliability	M	SD	Factor loading
AI identity	.956			
AI engagement		4.28	0.57	.933
AI affiliation		4.02	0.68	.792
AI actualisation		4.28	0.54	.952
AI goal setting		4.16	0.64	.915
AI engagement	.881			
Eng1		4.32	0.61	.854
Eng2		4.34	0.62	.872
Eng3		4.26	0.63	.885
Eng4		4.21	0.68	.821
AI affiliation	.890			
Aff1		4.03	0.77	.822
Aff2		3.95	0.77	.853
Aff3		4.07	0.74	.852
AI actualisation	.917			
Act1		4.24	0.64	.851
Act2		4.28	0.63	.848
Act3		4.30	0.60	.783
Act4		4.28	0.63	.793
AI goal setting	.904			
Goal1		4.17	0.71	.813
Goal2		4.15	0.69	.889
Goal3		4.16	0.71	.911

Note. M = mean; SD = standard deviation.

Table 5 Modification indices for each pair of survey items

Item pair	Modification index
Aff2 & Act4	7.36
Aff2 & Act2	6.615
Aff1 & Act4	6.16
Act4 & Goal1	6.04
Aff3 & Goal3	5.72
Aff3 & Act4	5.53
Eng3 & Aff2	5.48
Act1 & Goal2	5.38
Aff2 & Goal2	5.24
Eng4 & Aff3	4.52
Eng3 & Goal1	4.37
Aff3 & Act3	4.18
Eng1 & Eng4	4.03

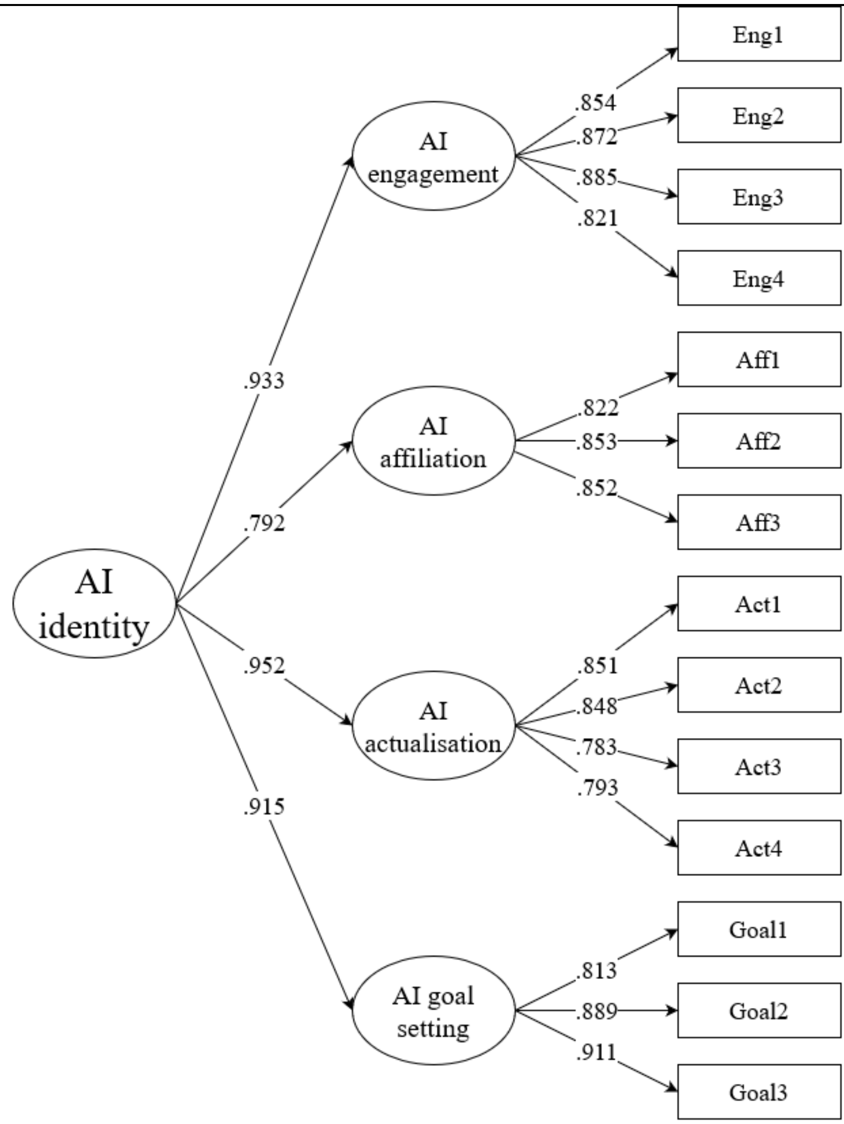

Fig. 2 Factor structure of the AI identity model

Comparing Pre- and Post-course Response to the AI Identity Scale

To determine whether a parametric or non-parametric statistical analysis was more suitable when comparing the students' survey score before and after the course, the Shapiro–Wilk test for normality (Shapiro & Wilk, 1965) was employed. It indicated a significant divergence from normality in the students' pre- and post-course score in the entire AI Identity Scale as well as in each of the four subscales (Table 6), supporting the use of non-parametric tests such as the Wilcoxon signed-rank test (Wilcoxon, 1945).

Table 6 The Shapiro–Wilk test for normality of the entire AI Identity Scale and the four subscales

Scale/subscale	Shapiro–Wilk test	
	Pre-course	Post-course
AI Identity Scale	.968***	.946***
AI engagement subscale	.907***	.881***
AI affiliation subscale	.931***	.919***
AI actualisation subscale	.900***	.874***
AI goal setting subscale	.914***	.885***

Note. *p < .05; **p < .01; ***p < .001.

Table 7 presents the students' response to AI Identity Scale and individual subscales before and after the course under study. The survey overall exhibited significant increase, demonstrating the students had a significantly higher sense of AI identity after participating in the AI literacy course. After breaking down the survey into subscales using the result from CFA, three of the four subscales (namely, AI engagement, AI affiliation, and AI goal setting) showed a statistically significant increase post-course. The students reported they could immerse themselves and felt engaged while learning about AI, presumably because the project-based course offered them the chance to formulate a solution to a self-defined problem with AI-powered platforms. Similarly, the students' heightened sense of affiliation to AI-learning and -using peers could be attributed to the collaborative design of the AI problem-solving project. Perhaps unsurprisingly, the students' successful completion of the project also enhanced their tendency to apply AI in their future professions and set it as one their career goals. Unlike the other three subscales, the AI actualisation subscale, which measured the students' propensity to use AI to solve personally meaningful problems, had no significant change after the course. However, this subscale had a high pre-course score, suggesting the ceiling effect may be behind the absence of statistical significance (Ho & Yu, 2014). A detailed discussion of the potential reasons behind is in the Implications of Study section.

Table 7 Means, standard deviations, and Wilcoxon signed-rank test Z-scores of the pre- and post-course AI Identity Scale

	Pre-course		Post-course			
Subscale (max. score = 5)	*M*	*SD*	*M*	*SD*	M_{diff}	*Z*
AI engagement	4.17	0.62	4.28	0.57	0.11	-3.18***
AI affiliation	3.74	0.74	4.02	0.68	0.28	-5.62***
AI actualisation	4.24	0.57	4.28	0.54	0.04	-1.02
AI goal setting	4.01	0.71	4.16	0.64	0.15	-3.60***
Overall mean and standard deviation	**4.06**	**0.57**	**4.20**	**0.54**	**0.14**	**-4.74*** **

To complement and corroborate the qualitative findings, we have also collected students' self-reflections to their formation and reinforcement of AI identity as qualitative support. Selected reflective essays are listed in Table 8. It is worth noting that East Asian culture, compared to other cultures, is less expressive of emotions (particularly positive emotions) and more prone to self-effacement (Kitayama & Salvador, 2024; Schouten et al., 2020; Yik & Chen, 2023). The students' discussion of their AI identity in self-reflections may have been influenced by this cultural norm.

Table 8 Selected self-reflections of students

After the course, I want to apply my knowledge and skills in AI to solve everyday problems, to make my life easier, and to improve others' lives. I want to use AI to develop interesting solutions to complex problems.
Having completed the project, I, even as someone without a strong background in AI or technology, no longer fear applying AI for solving various problems.
By conducting the project in groups, we were able to share our perspectives and collaborate with our peers. After learning from each other's knowledge and skills in AI, I feel we have become more proficient AI users.
The collaborative project allowed us to learn from one another. For instance, my peers have suggested ideas that I couldn't think of on my own. This prompts me to discuss with them in a more in-depth way.

Implications of Study

Our course allowed the students to actively participate in collaborative problem-solving projects, where they became acquainted with using AI for problem-solving of various kinds, from study-related to career-related and to society-related. Throughout the course, the students were not passive recipients of knowledge, but took the initiative to identify problems to be solved, design AI solutions, and reflect on the ethical implications of the problem-solving process. This active participation of students, guided by instructors who acted as mentors rather than traditional teachers, enabled students to migrate from the periphery of the AI community to its centre, and was behind the enhancement in their level of AI engagement.

The collaborative nature of the group project and the oral presentation and peer evaluation at the end of the course provided students opportunities to learn from not only their group members but also other students in the course who they did not work with. Through working closely with their groupmates over the AI problem-solving process, each student first developed a feeling that they and their groupmates belong to the same community. That they were also required to provide constructive feedback to the AI solutions and reflections from peers further connected the students across the groups to one another. As a result, the students were able to perceive other students as members of the same AI-interacting and AI-learning social group, fostering their sense of attachment to the entire class and improving their level of AI affiliation, which reinforces the social aspect of learning and encourages continued interaction with AI.

Although the course did not explicitly focus on careers in AI, the freedom given to students to select problems and devise AI solutions may have helped them in determining their career goals, which may or may not be directly related to AI. Even if their future careers do not directly involve computer science or programming, given the increasing prevalence of AI in society, they likely still need to work with AI and solve problems at work using AI (Acemoglu et al., 2023). The psychological readiness to apply AI, therefore, becomes paramount (Kong et al., 2024; Wang et al., 2023). The students' success in self-formulating an AI solution to a self-defined problem conferred them a sense of achievement and reinforced their belief that they are capable of using AI to solve problems in their future careers, effectively helping mould their future identity. Furthermore, as mentioned in the Background of Study, students, particularly high school students, are highly influenced by their peers when deciding their career goals (Yeager et al., 2017). Thus, we suggest that the problem-solving project and the resulting sense of affiliation in the students together contributed to a heightened level of AI goal setting.

On the other hand, we attributed the absence of change in the level of AI actualisation to the ceiling effect resulted from high pre-course score (Ho & Yu, 2014), which, in turn, may be due to students' frequent adoption of and positive attitude towards using AI (particularly generative AI) even prior to participating in the course. Indeed, recent studies of high school and university students have reported that they routinely use AI for study-related purposes (Darvishi et al., 2024; McDonald et al., 2025; Reiter et al., 2025) and views this usage of AI positively (Chan & Hu, 2023; He et al., 2024; Li et al., 2025). Although some students are aware of the potential pitfalls of AI in education (Baek et al., 2024; Kim et al., 2025), they in general habitually resort to AI as a solution when circumstances allow. Beyond schools, high school and university students have also been found to frequently use generative AI for more psychological and personal purposes, including informal psychological counselling (Kuhail et al., 2024, Rackoff et al., 2025) and considering AI as friends or companions (Bakir & McStay, 2025; Bhat et al., 2025; Herbener & Damholdt, 2025). These pre-existing interactions with AI very likely contributed to the students' high pre-course level of AI actualisation.

Taken together, the present study confirms the importance of close peer collaboration and active participation to the successful formation of AI, and advocate for the inclusion of student-led problem-solving group projects in AI literacy curricula.

Conclusion, Contribution, Limitation and Future Work

This study contributes to AI literacy education in two ways: as a new resource for evaluating AI literacy education and as a guide to curricular design in AI literacy education. Firstly, it is, to the best of our knowledge, the first study of AI identity in the context of AI literacy. In doing so, it establishes the AI Identity Scale as a valid and reliable instrument. Four subscales of AI identity were uncovered, namely AI engagement, AI affiliation, AI actualisation, and AI goal setting. These four dimensions collectively construct the overall AI identity, which is necessary for individuals to be psychologically prepared to utilise AI, including for problem-solving in both professional and personal spheres. As a readily usable instrument, the AI Identity Scale, together with the other instruments previously reported (Kong et al., 2024), could be a valuable resource for measuring students' complete psychological readiness to apply AI to solve problems.

Secondly, the study's findings recommend that designers of AI literacy curricula incorporate problem-solving projects as a learning activity to enhance participants' level of AI identity. Comparison of students' level of AI identity before and after participating in our problem-solving project-based AI literacy course demonstrated significant improvement in overall AI identity and in individual dimensions of AI engagement, AI affiliation, and AI goal setting in university and senior secondary students after the course. The project-based nature of our course featured authentic experience, practical use of AI, and collaboration with peers, closely aligning with SLT, which argues that learning requires authentic contexts and activities alongside guidance and mentoring from experts (Dede, 2009), and that as learners engage with the practices of a certain community, they acquire knowledge and skills and gradually migrate from the periphery of that community to the centre (Mina-Herrera, 2020; Lave & Wenger, 1991).

Two limitations of the study are acknowledged. Firstly, as all participants of the study come from Hong Kong, the generalisability of the scale and results presented may have been influenced by this geographical homogeneity. One direction of future research could be the administration of the AI Identity Scale in other cultural and geographical contexts, ensuring the findings are generalisable and applicable across locations and cultures. This could be coupled with longitudinal studies to investigate if and how AI identity influences students' long-term behaviour and career choices. Secondly, we believe there is a need to establish a clear relationship between AI identity and other dimensions and constructs of AI literacy, including but not limited to AI empowerment, the use of AI concepts to solve problems with AI, and the competence in problem-solving with AI (Kong et al., 2024). Although it is outside the scope of this study, such an analysis could be carried out under a framework of a structural equation model of AI literacy as a whole.

Appendix 1: Artificial Intelligence Identity Scale

AI engagement

1. The content of AI programmes makes me more interested in learning AI.
2. I think learning AI is fun.
3. I am really drawn to learning AI.
4. I feel engaged in learning AI.

AI affiliation

5. I feel connections with my peers when participating in AI learning activities with them.

6. Learning AI with my peers gives me a strong sense of belonging.
7. I like to discuss AI-related topics with my peers.

AI actualisation

8. In the future, I want to learn more about AI.
9. In the future, I want to use AI knowledge to solve real-world problems.
10. In the future, I want to use my AI knowledge to design new applications that interest me personally.
11. In the future, AI will be part of my life.

AI goal setting

12. In the future, I want to work in a job where I can use AI concepts and application development skills.
13. In the future, I want to collaborate with colleagues who also like AI.
14. In the future, I want to participate in activities / discussions with colleagues who share an interest in AI.

Abbreviations

AI: Artificial intelligence; CFA: Confirmatory factor analysis; PBL: Project-based learning; SLT: Situated learning theory; STEM: Science, technology, engineering, and mathematics.

Author's contributions

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Availability of data and materials

Data will be available if the request is reasonable.

Declarations

Competing interests

The authors declare no competing financial interests or personal relationship that could have influenced the results reported in this article.

Statements on open data and ethics

Data that support the findings of this study are not available. Excerpt of the test is shared in the appendix. Justified request for the entire test will be entertained. Ethical approval for this study was granted by the Human Research Ethics Committee of the authors' university (Ref. no. A2020-2021-0204 and 2021-2022-0325). Participation in this study is entirely voluntary, and participants can opt out anytime during the study. Informed consent has been obtained from all participants.

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References

Acemoglu. D., Autor, D., & Johnson, S. (2023). *Can we have pro-worker AI? Choosing a path of machines in service of minds*. MIT Shaping the Future of Work Initiative. https://shapingwork.mit.edu/wp-content/uploads/2023/09/Pro-Worker-AI-Policy-Memo.pdf

Adams, A., Astruc, L., Garrido, C., Sweeney, B. (2011). Situated learning in virtual worlds and identity reformation. In A. Peachey & M. Childs (Eds.), *Reinventing ourselves: Contemporary concepts of identity in virtual worlds*. Springer. https://doi.org/10.1007/978-0-85729-361-9_14

Alfrey, K.-L., Waters, K. M., Condie, M., & Rebar, A. L. (2023). The role of identity in human behavior research: A systematic scoping review. *Identity*, *23*(3), 208–223. https://doi.org/10.1080/15283488.2023.2209586

Aluja, A., Blanch, A., & García, L. F. (2005). Reanalyzing the 16pf-5 second order structure: Exploratory versus confirmatory factorial analysis. *European Journal of Psychology of Education*, *20*(4), 343–353. https://doi.org/10.1007/bf03173561

Bae, C. L., & Lai, M. H. C. (2020). Opportunities to participate in science learning and student engagement: A mixed methods approach to examining person and context factors. *Journal of Educational Psychology, 112*(6), 1128–1153. https://doi.org/10.1037/edu0000410

Baek, C., Tate, T., & Warschauer, M. (2024). "ChatGPT seems too good to be true": College students' use and perceptions of generative AI. *Computers and Education: Artificial Intelligence*, *7*, 100294, 1–9. https://doi.org/10.1016/j.caeai.2024.100294

Bakir, V., & McStay, A. (2025). Move fast and break people? Ethics, companion apps, and the case of Character.ai. *AI and Society*. Advance online publication. https://doi.org/10.1007/s00146-025-02408-5

Bell, R. L., Maeng, J. L., & Binns, I. C. (2013). Learning in context: Technology integration in a teacher preparation program informed by situated learning theory. *Journal of Research in Science Teaching*, *50*(3), 348–379. https://doi.org/10.1002/tea.21075

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588–606. https://doi.org/10.1037/0033-2909.88.3.588

Bhat, R., Kowshik, S., Suresh, S., Alamelu, G., Gite, S., & Albattat, A. (2025). Digital companionship or psychological risk? The role of AI characters in shaping youth mental health. *Asian Journal of Psychiatry*, *104*, 104356, 1–3. https://doi.org/10.1016/j.ajp.2024.104356

Branje, S., de Moor, E. L., Spitzer, J., Becht, A. I. (2021). Dynamics of identity development in adolescence: A decade in review. *Journal of Research on Adolescence*, *31*(4), 908–927. https://doi.org/10.1111/jora.12678

Brown, T. A. (2015). Model Revision and Comparison. In T. A. Brown, *Confirmatory factor analysis for applied research* (2nd ed., pp. 139–185). Guilford Publications.

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), https://doi.org/10.1177/0049124192021002005

Cain, M. K., Zhang, Z., & Yuan, K.-H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*, *49*, 1716–1735. https://doi.org/10.3758/s13428-016-0814-1

Carter, M., & Grover, V. (2015). Me, my self, and I(T): Conceptualizing information technology identity and its implications. *Management Information Systems Quarterly*, *39*(4), 931–958. https://doi.org/10.25300/MISQ/2015/39.4.9

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*, 43, 1–18. https://doi.org/10.1186/s41239-023-00411-8

Christiansen, C. (2000). Identity, personal projects and happiness: Self construction in everyday action. *Journal of Occupational Science*, *7*(3), 98–107. https://doi.org/10.1080/14427591.2000.9686472

Crocetti, E., Albarello, F., Meeus, W., & Rubini, M. (2023). Identities: A developmental social-psychological perspective. *European Review of Social Psychology*, *34*(1), 161–201. https://doi.org/10.1080/10463283.2022.2104987

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*, 297–334. https://doi.org/10.1007/BF02310555

Dai, Y., Chai, C.-S., Lin, P.-Y., Jong, M. S.-Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. *Sustainability*, *12*(16), 6597, 1–15. https://doi.org/10.3390/su12166597

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, G., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers and Education*, *210*, 104967, 1–18. https://doi.org/10.1016/j.compedu.2023.104967

De Corte, E. (2017). Constructive, self-regulated, situated, and collaborative learning: An approach for the acquisition of adaptive competence, *Journal of Education*, *192*(2–3), 33–47. https://doi.org/10.1177/0022057412192002-307

Dede, C. (2009). Immersive interfaces for engagement and learning. *Science*, *323*(5910), 66–69. https://doi.org/10.1126/science.1167311

Dou, R., Hazari, Z., Dabney, K., Sonnert, G., & Sadler, P. (2019). Early informal STEM experiences and STEM identity: The importance of talking science. *Science Education*, *103*(3), 623–637. https://doi.org/10.1002/sce.21499

Dyson, B., Griffin, L. L., & Hastie, P. (2004). Sport education, tactical games, and cooperative learning: Theoretical and pedagogical considerations. *Quest*, *56*(2), 226–240. https://doi.org/10.1080/00336297.2004.1049

Ellemers, N., Spears, R., & Doosje, B. (2002). Self and social identity. *Annual Review of Psychology, 53*(1), 161–186. https://doi.org/10.1146/annurev.psych.53.100901.135228

Erikson, E. H. (1968). *Identity: Youth and crisis.* W. W. Norton.

European Commission, & European Education and Culture Executive Agency. (2023). *AI report – By the European Digital Education Hub's Squad on artificial intelligence in education*. Publications Office of the European Union. https://data.europa.eu/doi/10.2797/828281

Handley, K., Sturdy, A., Fincham, R., & Clark, T. (2006). Within and beyond communities of practice: Making sense of learning through participation, identity and practice. *Journal of Management Studies*, *43*(3), 641–653. https://doi.org/10.1111/j.1467-6486.2006.00605.x

Hazari, Z., Sonnert, G., Sadler, P. M., & Shanahan, C. (2010). Connecting high school physics experiences, outcome expectations, physics identity, and physics career choice: A gender study. *Journal of Research in Science Teaching, 47*(8), 978–1003. https://doi.org/10.1002/tea.20363

He, A. J., Zhang, Z., Anand, P., & McMinn, S. (2024). Embracing generative artificial intelligence tools in higher education: a survey study at the Hong Kong University of Science and Technology. *Journal of Asian Public Policy*. Advance online publication. https://doi.org/10.1080/17516234.2024.2447195

Herbener, A. B., & Damholdt, M. F. (2025). Are lonely youngsters turning to chatbots for companionship? The relationship between chatbot usage and social connectedness in Danish high-school students. *International Journal of Human-Computer Studies*, *196*, 103409, 1–13. https://doi.org/10.1016/j.ijhcs.2024.103409

Herrington, J., & Oliver, R. (2000). An instructional design framework for authentic learning environments. *Educational Technology Research and Development*, *48*, 23–48. https://doi.org/10.1007/BF02319856

Ho, A. D., & Yu, C. C. (2014). Descriptive statistics for modern test score distributions: Skewness, kurtosis, discreteness, and ceiling effects. *Educational and Psychological Measurement*, *75*(3), 365–388. https://doi.org/10.1177/0013164414548576

Hogg, M. A., & Smith, J. R. (2007). Attitudes in social context: A social identity perspective. *European Review of Social Psychology*, *18*(1), 89–131. https://doi.org/10.1080/10463280701592070

Hornsey, M. J. (2008). Social identity theory and self-categorization theory: A historical review. *Social and Personality Psychology Compass*, *2*(1), 204–222. https://doi.org/10.1111/j.1751-9004.2007.00066.x

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jenkins, R. (2008). Groups and categories. In R. Jenkins, *Social identity* (3rd ed., pp. 102–117). Routledge.

Kaplan, A., & Flum, H. (2012). Identity formation in educational settings: A critical focus for education in the 21st century. *Contemporary Educational Psychology*, *37*(3), 171–175. https://doi.org/10.1016/j.cedpsych.2012.01.005

Karaś, D., Topolewska-Siedzik, E., & Negru-Subtirica, O. (2018). Contemporary views on personal identity formation. *Studia Psychologica: Theoria et praxis*, *18*(1), 5–25. https://doi.org/10.21697/sp.2018.18.1.01

Kim, A. Y., Sinatra, G. M., & Seyranian, V. (2018). Developing a STEM identity among young women: A social identity perspective. *Review of Educational Research*, *88*(4), 589–625. https://doi.org/10.3102/0034654318779957

Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on Generative AI-assisted academic writing. *Education and Information Technologies*, *30*, 1265–1300. https://doi.org/10.1007/s10639-024-12878-7

Kitayama, S., & Salvador, C. E. (2024). Cultural psychology: Beyond East and West. *Annual Review of Psychology*,*75*, 495–526. https://doi.org/10.1146/annurev-psych-021723-063333

Kong, S.-C., Cheung, W. M.-Y., & Tsang, O. (2022). Evaluating an artificial intelligence literacy programme for empowering and developing concepts, literacy and ethical awareness in senior secondary students. *Education and Information Technologies*, *28*, 4703–4724. https://doi.org/10.1007/s10639-022-11408-7

Kong, S.-C., Cheung, M.-Y. W., & Tsang, O. (2024). Developing an artificial intelligence literacy framework: Evaluation of a literacy course for senior secondary students using a project-based learning approach. *Computers and Education: Artificial Intelligence*, *6*, 100214, 1–11. https://doi.org/10.1016/j.caeai.2024.100214

Kong, S.-C., Cheung, W. M.-Y., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. *Computers and Education: Artificial Intelligence*, *2*, 100026, 1–12. https://doi.org/10.1016/j.caeai.2021.100026

Kong, S.-C., & Wang, Y. Q. (2020). Formation of computational identity through computational thinking perspectives development in programming learning: A mediation analysis among primary school students. *Computers in Human Behavior*, *106*, 106230, 1–12. https://doi.org/10.1016/j.chb.2019.106230

Kuhail, M. A., Alturki, N., Thomas, J., & Alkhalifa, A. K. (2024). Human vs. AI counseling: College students' perspectives. *Computers in Human Behavior Reports*, *16*, 100534, 1–11. https://doi.org/10.1016/j.chbr.2024.100534

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence*, *3*, 100101, 1–15. https://doi.org/10.1016/j.caeai.2022.100101

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation.* Cambridge University Press. https://doi.org/10.1017/CBO9780511815355

Li, Y., Castulo, N. J., & Xu, X. (2025). Embracing or rejecting AI? A mixed-method study on undergraduate students' perceptions of artificial intelligence at a private university in China. *Frontiers in Education*, *10*, 1505856, 1–11. https://doi.org/10.3389/feduc.2025.1505856

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, 140, 5–55.

Lu, W., & Lin, C. (2025). How do artificial intelligence literacy constructs work—based on a survey of university non-expert students. *Education and Information Technologies*. Advance online publication. https://doi.org/10.1007/s10639-025-13323-z

Mavri, A., Ioannou, A., & Loizides, F. (2021). Value creation and identity in cross-organizational communities of practice: A learner's perspective. *The Internet and Higher Education*, *51*, 100822, 1–20. https://doi.org/10.1016/j.iheduc.2021.100822

McDonald, N., Johri, A., Ali, A., & Hingle Collier, A. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. *Computers in Human Behavior: Artificial Humans*, *3*, 100121, 1–11. https://doi.org/10.1016/j.chbah.2025.100121

McLoughlin, C., & Luca, J. (2006). Applying situated learning theory to the creation learning environments to enhance socialisation and self-regulation. In A. Herrington & J. Herrington (Eds.), *Authentic learning environments in higher education* (pp. 194–213). IGI Global. https://doi.org/10.4018/978-1-59140-594-8.ch015

Mina-Herrera, S. P. (2020). Situated learning theory. In J. Egbert & M. Roe (Eds.), *Theoretical models for teaching and research*. Washington State University. https://opentext.wsu.edu/theoreticalmodelsforteachingandresearch/chapter/situated-learning-theory/

Mosafer, H., & Sarabadani, J. (2021). Identity in the digital age: A review of information technology identity (ITID) research in information systems. In *Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 2627–2636). University of Hawaii at Manoa. http://hdl.handle.net/10125/70935

Myint, E. T., & Robnett, R. D. (2024). Correlates of adolescents' STEM career aspirations: The importance of academic motivation, academic identity, and gender. *European Journal of Psychology of Education*, *39*, 189–209. https://doi.org/10.1007/s10212-023-00681-w

Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, *55*(3), 1082–1104. https://doi.org/10.1111/bjet.13411

Olson, E. T. (2023). Personal identity. In E. N. Zalta & U. Nodelman (Eds.), *The Stanford encyclopedia of philosophy* (Summer 2023 ed.). Stanford University. https://plato.stanford.edu/archives/sum2023/entries/identity-personal/

Orgill, M. (2007). Situated cognition. In G. M. Bodner & M. Orgill (Eds.), *Theoretical frameworks for research in chemistry/science education* (pp. 179–194). Prentice Hall.

Oyserman, D. (2009). Identity-based motivation: Implications for action-readiness, procedural-readiness, and consumer behavior. *Journal of Consumer Psychology*, *19*(3), 250–260. https://doi.org/10.1016/j.jcps.2009.05.008

Pérez-Sanagustín, M., Muñoz-Merino, P. J., Alario-Hoyos, C., Soldani, X., & Delgado Kloos, C. (2015). Lessons learned from the design of situated learning environments to support collaborative knowledge construction. *Computers and Education*, *87*, 70–82. https://doi.org/10.1016/j.compedu.2015.03.019

Pfeifer, J. H., & Berkman, E. T. (2018). The development of self and identity in adolescence: Neural evidence and implications for a value-based choice perspective on motivated behaviour. *Child Development Perspectives*, *12*(3), 158–164. https://doi.org/10.1111/cdep.12279

Rackoff, G. N., Zhang, Z. Z., & Newman, M. G. (2025). Chatbot-delivered mental health support: Attitudes and utilization in a sample of U.S. college students. *Digital Health*. Advance online publication. https://doi.org/10.1177/20552076241313401

Rathbone, J. A., Cruwys, T., Stevens, M., Ferris, L. J., & Reynolds, K. J. (2023). The reciprocal relationship between social identity and adherence to group norms. *British Journal of Social Psychology*, *62*(3), 1346–1362. https://doi.org/10.1111/bjso.12635

Reiter, L., Jörling, M., Fuchs, C., Working group 'Artificial Intelligence in Higher Education', & Böhm, R. (2025). Student (mis)use of generative AI tools for university-related tasks. *International Journal of Human–Computer Interaction*. Advance online publication. https://doi.org/10.1080/10447318.2025.2462083

Rogers, L. O. (2018). Who am I, who are we? Erikson and a transactional approach to identity research. *Identity*, *18*(4), 1–11. https://doi.org/10.1080/15283488.2018.1523728

Rushton, E. A. C., Gibbons, S., Brock, R., Cao, Y., Finesilver, C., Jones, J., Manning, A., Marshall, B., Richardson, C., Steadman, S., Suh, S., & Towers, E. (2025). Collaborative identity development during a global pandemic: exploring teacher identity through the experiences of pre-service high school teachers in England. *European Journal of Teacher Education*, *48*(2), 267–290. https://doi.org/10.1080/02619768.2023.2175663

Schouten, A., Boiger, M., Kirchner-Häusler, A., Uchida, Y., & Mesquita, B. (2020). Cultural differences in emotion suppression in Belgian and Japanese couples: A social functional model. *Frontiers in Psychology*, *11*, 1048, 1–12. https://doi.org//10.3389/fpsyg.2020.01048

Schwartz, S. J., Donnellan, M. B., Ravert, R. D., Luyckx, K., & Zamboanga, B. L. (2012). Identity development, personality, and well-being in adolescence and emerging adulthood: Theory, research, and recent advances. In R. Lerner, A. Easterbrooks, & J. Mistry (Eds.), *Handbook of psychology. Volume 6. Developmental psychology* (2nd ed.). https://doi.org/10.1002/9781118133880.hop206014

Schwartz, S. J., Luyckx, K., & Crocetti, E. (2014). What have we learned since Schwartz (2001)? A reappraisal of the field of identity development. In K. C. McLean & M. Syed (Eds.), *The Oxford handbook of identity development* (pp. 539–561). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199936564.013.028

Sfard, A., & Prusak. A. (2005). Telling identities: In search of an analytic tool for investigating learning as a culturally shaped activity. *Educational Researcher*, *34*(4), 14–22. https://doi.org/10.3102/0013189X034004014

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3–4), 591–611. https://doi.org/10.1093/biomet/52.3-4.591

Simpson, A., & Bouhafa, Y. (2022). Youths' and adults' identity in STEM: A systematic literature review. *Journal for STEM Education Research*, *3*, 167–194. https://doi.org/10.1007/s41979-020-00034-y

Sindic, D., & Condor, S. (2014). Social identity theory and self-categorisation theory. In P. Nesbitt-Larking, C. Kinnvall, T. Capelos, & H. Dekker (Eds.), *The Palgrave handbook of global political psychology* (1st ed., pp. 39–54). https://doi.org/10.1007/978-1-137-29118-9_3

Starr, C. R., Hunter, L., Dunkin, R., Honig, S., Palomino, R., & Leaper, C. (2020). Engaging in science practices in classrooms predicts increases in undergraduates' STEM motivation, identity, and achievement: A short-term longitudinal study. *Journal of Research in Science Teaching*, *57*(7), 1093–1118. https://doi.org/10.1002/tea.21623

Taconis, R., & Bekker, T. (2023). Challenge Based Learning as authentic learning environment for STEM identity construction. *Frontiers in Education*, *8*, 1144702, 1–14. https://doi.org/10.3389/feduc.2023.1144702

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), *The social psychology of intergroup relations* (pp. 33–47). Brooks/Cole.

Tissenbaum, M., Sheldon, J., & Abelson, H. (2019). From computational thinking to computational action. *Communications of the ACM*, *62*(3), 34–36. https://doi.org/10.1145/3265747

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Basil Blackwell.

United Nations High-Level Advisory Body on Artificial Intelligence. (2023). *Interim report: Governing AI for humanity*. United Nations. https://www.un.org/sites/un2.un.org/files/ai_advisory_body_interim_report.pdf

Verplanken, B., & Sui, J. (2019). Habit and identity: Behavioral, cognitive, affective, and motivational facets of an integrated self. *Frontiers in Psychology*, *10*, 1504, 1–11. https://doi.org/10.3389/fpsyg.2019.01504

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour and Information Technology*, *42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

White House (2023). *Executive order on the safe, secure, and trustworthy development and use of artificial intelligence*. White House. https://www.govinfo.gov/content/pkg/FR-2023-11-01/pdf/2023-24283.pdf

Wilcoxon, F. (1945). Individual Comparisons by Ranking Methods. *Biometrics Bulletin*, *1*(6), 80–83. https://doi.org/10.2307/3001968

Yeager, D. S., Bundick, M. J., & Johnson, R. (2017). The role of future work goal motives in adolescent identity development: A longitudinal mixed-methods investigation. *Contemporary Educational Psychology*, *37*(3), 206–217. https://doi-org.ezproxy.eduhk.hk/10.1016/j.cedpsych.2012.01.004

Yik, M., & Chen, C. Z. (2023). Unraveling Chinese talk about emotion. *Frontiers in Psychology*, *14*, 1157863, 1–9. https://doi.org/10.3389/fpsyg.2023.1157863

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