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University students' intentions to learn artificial intelligence: the roles of supportive environments and expectancy–value beliefs

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Abstract

Despite the importance of artificial intelligence (AI) for university students to thrive in the future workplace, few studies have been conducted to assess and foster their intentions to learn AI. Guided by the situated expectancy–value theory, this study adopted both variable- and person-centered approaches to explore the role of supportive environments and expectancy–value beliefs in fostering university students' intentions to learn AI. The data were drawn from 494 university students. In Study 1, the variable-centered approach of structural equation modeling showed the critical role of supportive environments and expectancy–value beliefs in promoting students' intentions to learn AI. In Study 2, the person-centered approach of latent profile analysis identified three subgroups of students based on their levels of supportive environments and expectancy–value beliefs. Consistent with Study 1, students who perceived more supportive environments and higher levels of expectancy–value beliefs had stronger intentions to learn AI. We also documented the influence of study of field, gender, and year level on students' perceptions of supportive environments, expectancy-value beliefs and intentions to learn AI. The implications of these findings in improving students' intentions to learn AI are discussed.

Keywords: Artificial Intelligence (AI), Intentions to learn AI, Supportive environments, expectancy–value beliefs, University students

Introduction

Artificial Intelligence (AI) is reshaping job markets. According to a report by the McKinsey Global Institute, up to 30 percent of current work activities could be automated by 2030, potentially displacing 400 to 800 million workers (Manyika et al., 2017). Given the transformative influence of AI on future workplaces, international organizations such as the OECD (Vincent-Lancrin & Van der Vlies, 2020), the World Economic Forum (2023), UNICEF (Lemaignan et al., 2021), and UNESCO (Miao et al., 2021) have acknowledged the importance of AI-related skills in the 21st century.

As the demand for AI skills continues to increase, it is crucial for higher education institutions to future-proof their graduates by motivating them to learn about AI (Bates et al., 2020). However, existing research on AI education has mostly focused on

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the curriculum and technical aspects (Salas-Pilco & Yang, 2022; Zawacki-Richter et al., 2019). Less attention has been devoted to understanding motivational factors that underpin students' desire to learn about AI, even though existing research has demonstrated the importance of learning environments and motivational beliefs in fostering students' intentions to learn about new technology (e.g., Huang et al., 2020; Kelly et al., 2023). This study contributes to the literature by investigating how expectancy–value beliefs can foster students' intentions to learn AI based on the situated expectancy–value theory (SEVT; Eccles & Wigfield, 2020).

SEVT is one of the most prominent theoretical frameworks for understanding students' motivation, emphasizing the situated expectancies for success (e.g., self-efficacy) and subjective task value (e.g., perceived usefulness) in students' learning intentions, choices, and effort (Eccles & Wigfield, 2020). SEVT provides a comprehensive framework that includes both expectancy and value components of motivation, which has demonstrated strong predictive power in explaining individuals' intentions to learn (Eccles & Wigfield, 2020). Furthermore, SEVT acknowledges the situated nature of expectancy and value beliefs and sheds light on the interplay between internal motivation and external environmental factors on individual learning (Eccles & Wigfield, 2023). Therefore, SEVT provides a solid theoretical foundation for exploring the relationship among supportive environments, expectancy–value beliefs, and students' intentions to learn AI.

Although SEVT has been used to examine student learning in various subjects, such as literacy (Li et al., 2023; Yeung et al., 2022), STEM (Fong et al., 2021; Wang et al., 2023; Wille et al., 2020), and foreign language (Li et al., 2022), few studies have explored their influence on students' intentions to learn AI. Existing research has indicated that students' expectancy and value beliefs are domain-specific, demonstrating that high levels of expectancy and value beliefs in one subject may not necessarily translate to high levels in another subject (Wigfield & Eccles, 2000). Furthermore, AI courses are often offered as elective courses rather than core requirements in many academic programs, which means students have the flexibility to choose whether or not to take AI courses based on their interests and career goals. This suggests that students' expectancy and value beliefs in learning AI might be different from those in other subjects. However, few studies have specifically explored the influence of these beliefs on students' intentions to learn AI. This study seeks to fill this gap by exploring the role of supportive environments in shaping students' expectancy–value beliefs and, ultimately, their intentions to learn AI in the context of higher education. By identifying the critical factors that potentially promote or inhibit students' intentions to learn AI, this study could offer higher education institutions valuable insights to design effective interventions for improving students' motivation to learn about AI.

This study combines the strengths of both variable- and person-centered designs. Study 1 adopted a variable-centered approach to explore the relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI. Study 2 conducted a person-centered approach to identify distinct subgroups of students who might exhibit different perceptions of supportive environments and expectancy–value beliefs. Integrating the two approaches could provide a comprehensive understanding of the role of situated expectancy–value beliefs in fostering students' intentions to learn AI, which is sensitive to both general trends (i.e., variable-centered approach) and individual differences (i.e., person-centered approach).

Literature review

Intentions to learn AI and expectancy–value beliefs

Intentions refer to one's desire or aim to engage in specific behaviors, indicating the degree of effort and perseverance individuals are willing to dedicate towards attaining their desired behaviors (Fishbein & Ajzen, 2010). Intentions have been widely used in educational technology (e.g., Ifinedo, 2018; Kwok & Yang, 2017) as a proxy for actual behaviors.

Intentions to learn AI is defined as willingness or predisposition to learn AI (Chai et al., 2020). While past studies have demonstrated the importance of motivational factors in individuals' intentions to learn AI (see Kelly et al., 2023, for a review), most of them have combined various types of motivational factors into a single model without explicitly applying a specific motivational theory as a guiding framework. For example, Ni and Cheung (2023) highlighted the importance of perceived usefulness, perceived ease of use, and technology anxiety, among others. Lin et. al. (2021) emphasized the importance of confidence, intrinsic motivation, career motivation, and relevance. However, these studies did not draw explicitly on an a-priori theoretical framework.

Without a clear theoretical framework, it becomes difficult to implement effective intentions as different motivational theories may be more effective in different environments. This gap in the literature highlights the need for a theoretical framework, such as the SEVT, to guide the research and enhance our understanding of the complex interplay between motivational factors and supportive environments in promoting AI education (Eccles & Wigfield, 2020). The present study addresses this gap by drawing on the situated expectancy–value framework, which has been widely used to understand students' learning and motivation (Eccles & Wigfield, 2020).

SEVT emphasizes the role of students' expectancies for success (i.e., beliefs about whether they can succeed in a task) and subjective task values (i.e., beliefs about whether a task is interesting, useful, or worthwhile to engage) in understanding effort, choice, and persistence in learning activities (Wigfield & Eccles, 2000). In the context of learning AI, students' expectancy beliefs are operationalized in terms of self-efficacy in learning AI, and value beliefs are operationalized as the perceived usefulness of AI (Chai et al., 2021). *Self-efficacy* in learning AI refers to one's judgment about one's ability to master AI, while the *perceived usefulness* of AI refers to the extent to which an individual believes that using AI would enhance their performance (Chai et al., 2021). Previous research has indicated that students tend to have stronger intentions to learn AI if they have higher levels of self-efficacy and if they perceive it as useful (Chai et al., 2020, 2022a; Ni & Cheung, 2023).

Supportive environments and intentions to learn AI

Aside from individual beliefs, the environment also plays a critical role in learning (King, 2022; King et al., 2019; King & McInerney, 2014). Past studies have found that supportive environments, such as facilitating conditions and supportive social norms, play a pivotal role in fostering individuals' intentions to learn AI (Chatterjee & Bhattacharjee, 2020; Teo, 2010). *Facilitating conditions* refer to the accessibility and availability of support (e.g., access to technology resources and technical support) in the environment that facilitates learning AI (Venkatesh et al., 2003). Teo (2010) found that facilitating conditions affect students' intentions to adopt the technology.

Supportive social norms are defined as the extent to which a student perceives other members of his/her social group want them to learn more about AI (Sohn & Kwon, 2020). Existing research has indicated that students' learning is facilitated when their peers, teachers, and school leaders support their learning through positive social norms (King et al., 2019; King & McInerney, 2014; Skinner et al., (2022). Humans are inherently social, and the environment provides them with cues as to what to do. When students perceive that their significant others perceive AI as important, they develop a stronger intention to learn about AI (Chai et al, 2022b).

Applying situated expectancy–value theory to understand intentions to learn AI

Recently, Eccles and Wigfield (2020) updated and renamed "expectancy–value theory" to "situated expectancy–value theory" or SEVT to emphasize the situated nature of expectancy–value beliefs. SEVT posits that students' expectancy–value beliefs are shaped by the environments in which they are situated. Compared with the original expectancy–value theory, SEVT emphasized more about the role of supportive environments in influencing learning outcomes via shaping students' expectancy–value beliefs (Eccles & Wigfield, 2020).

Although the critical role of supportive environments and expectancy–value beliefs in learning AI has been highlighted, most of these studies focused on their direct effects on students' intentions to learn AI (e.g., Chai et al. 2022b; Kelly et al., 2023). Little attention has been devoted to exploring the interplay between supportive environments and expectancy–value beliefs in fostering students' intentions to learn AI. This leads to a less nuanced understanding of the complex mechanism between supportive environments and expectancy–value beliefs and how they could collectively influence students' motivation to learn AI. SEVT addresses these shortcomings by highlighting the critical role played by the environment and motivational beliefs in understanding intentions to learn AI.

Demographic factors: field of study, gender, and year level

Aside from expectancy–value beliefs and learning environments, demographic factors may also play a role in understanding students' intentions to learn AI. Demographic factors, such as field of study, gender, and year level might be critical factors given that previous studies have shown that students' intentions toward technology differ due to their varied learning experiences (Owens & Lilly, 2017). For instance, Orji (2010) found that social science students are more influenced by supportive social norms, while science students place greater importance on perceived usefulness. Regarding gender, Terzis and Economides (2011) found that females had higher ratings for supportive environments, while males scored higher in the perceived usefulness of technology. Year level has also been researched. For example, Mei (2019) found that senior students have higher levels of perceived usefulness than junior students. Although the influence of demographic factors on technology acceptance has been widely researched, few studies have specifically focused on students' intentions to learn AI.

Variable- and person-centered approaches

In existing research, variable-centered approaches such as structural equation modeling (SEM) and regression modeling have been widely used to explore factors that influence students' intentions to learn AI (e.g., Chatterjee & Bhattacharjee, 2020). This strand of research aims to explore the general pattern of relationships among variables and assumes that the relationship between independent (i.e., supportive social norms, facilitating conditions, self-efficacy, and perceived usefulness) and dependent variables (i.e., intentions to learn AI) is similar across the entire population.

However, variable-centered approaches overlook the existence of individual differences as not all students experience the same types of environments and endorse the same beliefs (Eccles & Wigfield, 2020). Studies that use a person-centered approach, such as latent profile analysis (LPA), have found the existence of different subgroups of individuals characterized by distinct expectancy–value beliefs (Schweder & Raufelder, 2022). This approach could also be applied to the context of students' intentions to learn AI.

AI in Chinese higher education

The current study is conducted within the Chinese higher education context, where the government has identified AI as a key area of focus and a part of the national strategy, prioritizing investments in AI research and development, education and training, and infrastructure development (Wu et al., 2020). In 2017, the Chinese State Council issued the "Next Generation Artificial Intelligence Development Plan," which aims to make China the world's AI innovation center by 2030. To achieve this, the Chinese Ministry of Education released the "Artificial Intelligence Innovation Action Plan for Institutions of Higher Education" in 2018, which urges higher education institutions to create an environment that enables students to learn AI by establishing infrastructure and curricula that support AI, making teaching and research accessible to the students, and organizing competitions to encourage students to learn and use AI for innovative activities (Ministry of Education of China, 2018). In recent years, AI has become the fastest-growing major in Chinese universities, with 498 universities offering AI programs in 2022. Most universities have created AI-related elective courses for students who are interested in learning about AI. While higher education institutions have made great efforts to support students in learning AI, there have been limited empirical studies that examine how these supportive environments impact students' intentions to learn AI.

The present study

Two studies were designed to understand the relationship among supportive environments, expectancy–value beliefs, and students' intentions to learn AI. These two studies complemented each other with Study 1 using a variable-centered approach that focuses on general patterns and Study 2 using a person-centered approach that focuses on individual differences.

In Study 1, we adopted the variable-centered approach of SEM to investigate how supportive environments and expectancy–value beliefs influence students' intentions to learn AI. Figure 1 depicts the conceptual model. The following research questions were examined:

RQ1. To what extent do university students have similar/different perceptions of supportive environments, expectancy–value beliefs, and intentions to learn AI across field of study, gender, and year level?
RQ2. What are the relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI, and how do these relationships generalize across field of study, gender, and year level?

In Study 2, we used the person-centered approach of LPA to identify subgroups of individuals who display similar perceptions of supportive environments and expectancy–value beliefs. The following research questions were examined:

RQ3. What profiles characterize students' perceptions of supportive environments and expectancy–value beliefs in learning AI, and how does profile membership influence students' intentions to learn AI?
RQ4. How do field of study, gender, and year level predict profile membership?

Study 1: variable-centered study

Methods

Participants

The sample in this study included 494 students from 141 Chinese mainland universities. All participants were recruited using a convenience sampling strategy. The sample included 313 (63.4%) females and 181 (36.6%) males. In terms of field of study, 213 (43.1%) students were from humanities and social sciences (e.g., education and law), 247 (50%) were from science (e.g., medicine and engineering), and 34 (6.9%)

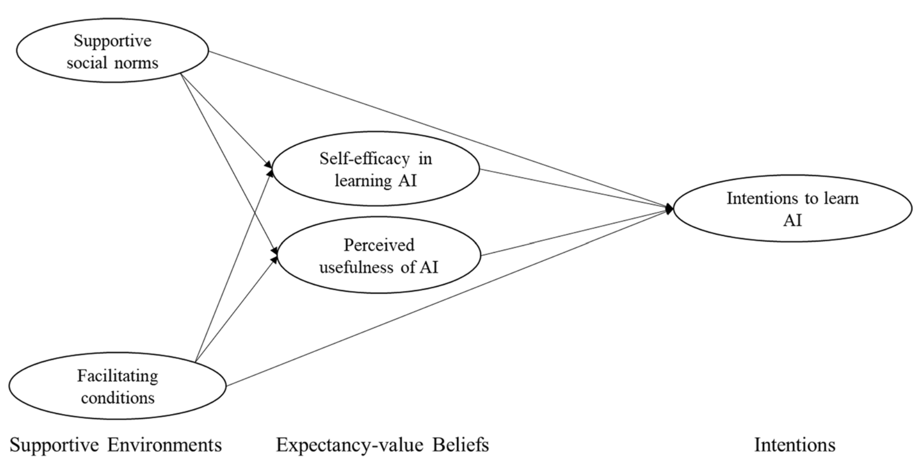

Fig. 1 Conceptual model

students did not report their majors. The number of students in Year 1, Year 2, Year 3, and Year 4 was 61 (12.3%), 156 (31.6%), 151 (30.6%), and 126 (25.5%), respectively. All procedures were approved by the ethics committee of the Chinese University of Hong Kong.

Instruments

Supportive environments Supportive social norms (4 items, e.g., "My school organizes enrichment lessons for me to learn more about AI", $\alpha = 0.83$) were adapted from Chai et al. (2020). Facilitating conditions (4 items, e.g., "I can gain access to information about AI easily", $\alpha = 0.88$) were developed based on the definition of Venkatesh et. al. (2003), focusing on students' accessibility to support and technology resources in learning AI.

Expectancy–value beliefs Expectancy beliefs were measured by self-efficacy in learning AI (4 items, e.g., "I am confident I can learn the basic concepts taught in the AI class", $\alpha = 0.84$), which is adapted from the Chai et al. (2021). Value beliefs were measured by the perceived usefulness of AI (4 items, e.g., "Using AI technology improves my performance", $\alpha = 0.83$), which is adapted from Chai et al. (2020).

Intentions to learn AI We adapted from Chai et al.'s (2020) behavioral intentions scale to gauge intentions to learn AI (4 items, e.g., "I will continue to learn about AI technology in the future", $\alpha = 0.82$).

All variables were rated on a 5-point scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The measures of supportive social norms, self-efficacy in learning AI, and perceived usefulness of AI were adapted from our previous studies, which focused on secondary students. We modified them to fit the learning contexts of university students. The scale of facilitating conditions was developed based on Venkatesh et. al.'s (2003) work as no existing instruments specifically focused on the facilitating conditions for learning AI. By adapting and developing these measures, we aimed to ensure that they were appropriate for measuring the constructs of interest in the university student population. To ensure the reliability and validity of the survey, we followed the International Test Commission (2018) guidelines during the development and adaptation of the items. All items were reviewed by two experts who specialized in educational technology and educational psychology. Based on their comments, we revised the items. We also recruited nine students from the participating universities to review and modify the wording of the items to make them easy to understand for students. The five-factor model showed satisfactory construct validity, with a $CFI = 0.931$, $TLI = 0.918$, and $RMSEA = 0.068$ (95% $CI = [0.062, 0.078]$), indicating that the scales are reliable measures of the intended constructs.

Demographic variables The demographic variables used in this study included field of study (sciences = 1, humanities and social sciences = 0), gender (male = 1, female = 0), and year of study [senior year (Year 3 and 4) = 1, junior year (Year 1 and 2) = 0].

The items of the key variables used in this study can be found in Additional file 1.

Statistical analyses

To address RQ1, we conducted multigroup CFA followed by testing latent mean differences. First, we conducted multigroup CFA analyses to test configural (i.e., basic model structure), metric (i.e., factor loadings), and scalar (i.e., factor loadings and item intercepts) invariance across field of study, gender, and year level, respectively. Support for scalar invariance reflects that the mean of the construct has the same meaning across groups, which is the basis of latent mean comparison. According to the criteria recommended by Chen (2007), $\Delta CFI \leq -0.01$, $\Delta RMSEA \leq 0.015$, and $\Delta SRMR \leq 0.03$ were the criteria for metric invariance, while $\Delta CFI \leq -0.01$, $\Delta RMSEA \leq 0.015$, and $\Delta SRMR \leq 0.01$ were the criteria for scalar invariance. Multigroup CFA is a prerequisite to the next step of comparing latent mean differences.

Next, latent mean differences were compared based on scalar invariance. The latent mean values for reference groups (i.e., female, humanities and social sciences, and junior) were constrained to zero, while the values for comparison groups (i.e., male, science, and senior) were freely estimated. The statistical significance of the latent mean differences was determined based on the z-statistic. Compared with traditional t-tests, the results of latent mean comparisons are more accurate and reliable as it accounts for the random error of measurement.

To address RQ2, SEM was conducted. In addition to the direct effects, we also examined whether expectancy–value beliefs mediated the influence of supportive environments on intentions to learn AI via Sobel tests (MacKinnon et al., 2002). Sobel tests calculated the indirect effects using regression weights and standard errors of the path between the independent variable and the mediator, and between the mediator and the dependent variable. Comparative Fit Index (*CFI*), Tucker-Lewis Index (*TLI*), root mean square error of approximation (*RMSEA*) were used to assess the model fit. Values of *CFI* and *TLI* greater than 0.90 and *RMSEA* less than 0.08 indicated a satisfactory fit (Hu & Bentler, 1995).

Furthermore, multigroup SEM analyses were conducted. We built two structural equation models with different restrictions to compare each group's invariance of path coefficients. A fully constrained model with all path coefficients equivalent across groups was compared against the fully unconstrained model. A significant $\Delta\chi^2$ between the two models indicated that the path coefficients were not equivalent. However, the assumptions of the two models (all paths are equal vs. all paths are different) were too strict. Additional Wald tests were conducted to test each path when invariance was found.

Results

Preliminary analysis

Table 1 summarizes the descriptive statistics and correlation matrix. The correlations among supportive environments, expectancy–value beliefs, and intentions to learn AI were significant, ranging from 0.26 to 0.63.

Table 1 Descriptive statistics and bivariate correlations

	1	2	3	4	5
1. Supportive social norms	–	0.63**	0.35**	0.54**	0.63**
2. Facilitating conditions		–	0.44**	0.54**	0.51**
3. Perceived usefulness of AI			–	0.26**	0.47**
4. Self-efficacy in learning AI				–	0.51**
5. Intentions to learn AI					–
M	3.58	3.55	4.17	3.30	3.92
SD	0.84	0.85	0.57	0.86	0.66

**$p < 0.01$

Latent mean differences

As shown in Table 2, configural, metric, and scalar invariance were achieved across the field of study, gender, and year level. Support for scalar invariance reflects that the mean of the construct has the same meaning across groups, satisfying the basis of latent mean comparison.

Table 3 shows the results of latent mean comparisons. Science students had higher supportive social norms ($z = 0.17$, $p < 0.05$) compared to their humanities and social sciences peers. Meanwhile, male students scored significantly higher in facilitating conditions ($z = 0.41$, $p < 0.001$), supportive social norms ($z = 0.41$, $p < 0.001$), self-efficacy in learning AI ($z = 0.41$, $p < 0.001$), and intentions to learn AI ($z = 0.23$, $p < 0.01$). For year of study, senior students had lower levels of supportive social norms ($z = -0.17$, $p < 0.05$) than their junior peers.

Table 2 Measurement invariance across field of study, gender, and year level

Models	**$\chi^2(df)$**	**CFI**	**TLI**	**RMSEA**	**SRMR**	**ΔCFI**	**ΔRMSEA**	**ΔSRMR**
Measurement invariance across field of study								
Humanities and social sciences	349.814 (159)***	0.920	0.904	0.075	0.057	–	–	–
Sciences	304.985 (159)***	0.945	0.934	0.061	0.049	–	–	–
Configural invariance	654.799 (318)***	0.933	0.920	0.068	0.053	–	–	–
Metric invariance	677.229 (333)***	0.931	0.922	0.067	0.062	0.002	0.001	−0.009
Scalar invariance	693.778 (348)***	0.931	0.925	0.066	0.063	0.000	0.001	−0.001
Measurement invariance across gender								
Female	402.161 (159)***	0.928	0.914	0.070	0.049	–	–	–
Male	377.063 (159)***	0.891	0.870	0.087	0.065	–	–	–
Configural invariance	779.224 (318)***	0.914	0.897	0.077	0.055	–	–	–
Metric invariance	791.171 (333)***	0.915	0.903	0.075	0.060	−0.001	0.002	−0.005
Scalar invariance	852.574 (348)***	0.906	0.897	0.077	0.063	0.009	−0.002	−0.003
Measurement invariance across year level								
Junior (year 1 and 2)	368.647 (160)***	0.917	0.901	0.078	0.055	–	–	–
Senior (year 3 and 4)	377.135 (160)***	0.926	0.913	0.070	0.053	–	–	–
Configural invariance	745.782 (320)***	0.922	0.907	0.073	0.054	–	–	–
Metric invariance	780.434 (335)***	0.918	0.907	0.073	0.067	0.004	0.000	−0.013
Scalar invariance	793.544 (350)***	0.919	0.912	0.072	0.066	−0.001	0.001	0.001

***$p < 0.001$; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual

Table 3 Latent mean difference across field of study, gender, and year level

	Facilitating conditions	Supportive social norms	Self-efficacy in learning AI	Perceived usefulness of AI	Intentions to learn AI
Field of study	0.08	0.17*	0.11	− 0.01	0.13
Gender	0.41***	0.25**	0.41***	0.04	0.23**
Year level	0.00	− 0.17*	− 0.11	0.02	− 0.04

The reference groups were humanities and social sciences, female, and junior students, respectively

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI

Figure 2 shows the relationship among supportive environments, expectancy–value beliefs, and intentions to learn AI. This model demonstrates a satisfactory fit with $CFI = 0.931$, $TLI = 0.919$, and $RMSEA = 0.068$ (95% $CI = [0.062, 0.075]$).

For the direct effect, both self-efficacy in learning AI ($\beta = 0.23$, $p < 0.001$) and perceived usefulness of AI ($\beta = 0.30$, $p < 0.001$) were significantly associated with intentions to learn AI. Supportive social norms had a significant influence on self-efficacy in learning AI ($\beta = 0.35$, $p < 0.001$), while its effect on perceived usefulness of AI was not significant ($\beta = 0.08$, $p > 0.05$). Facilitating conditions were positively linked with self-efficacy in learning AI ($\beta = 0.37$, $p < 0.001$) and perceived usefulness of AI ($\beta = 0.46$, $p < 0.001$).

Sobel tests were used to examine the mediation effects. The results indicated that self-efficacy in learning AI significantly mediated the relationship between supportive social norms and intentions to learn AI ($\beta = 0.08$, $p < 0.001$), and between facilitating conditions and intentions to learn AI ($\beta = 0.09$, $p < 0.01$). The effect of supportive norms on intentions to learn AI via perceived usefulness of AI was not significant ($\beta = 0.03$, $p > 0.05$), while perceived usefulness of AI significantly mediated the relationship between facilitating conditions and intentions to learn AI ($\beta = 0.14$, $p < 0.001$).

The relationship among supportive environments, expectancy–value beliefs, and intentions to learn AI across the field of study, gender, and year of study

We conducted multigroup SEM across field of study, gender, and year level. These models fit the data well with $CFI = 0.921$, $TLI = 0.914$, $RMSEA = 0.070$ (95% $CI = [0.063, 0.077]$) for field of study, $CFI = 0.902$, $TLI = 0.894$, $RMSEA = 0.078$ (95% $CI = [0.071, 0.084]$) for gender, and $CFI = 0.919$, $TLI = 0.912$, $RMSEA = 0.071$ (95% $CI = [0.065, 0.078]$) for year of study. Figure 3 shows the path coefficient of the model.

We then tested the differences in chi-square between the fully constrained and the fully unconstrained models across field of study, gender, and year of study. The results in Table 4 indicated significant differences across year of study with $\Delta\chi^2$ (8) = 16.28, $p < 0.05$, which suggested path variations between junior and senior students. The result of the Wald test showed that the effect of supportive social norms for junior students ($\beta = 0.27$, $p < 0.01$) was stronger than that for senior students ($\beta = -0.06$, $p > 0.05$).

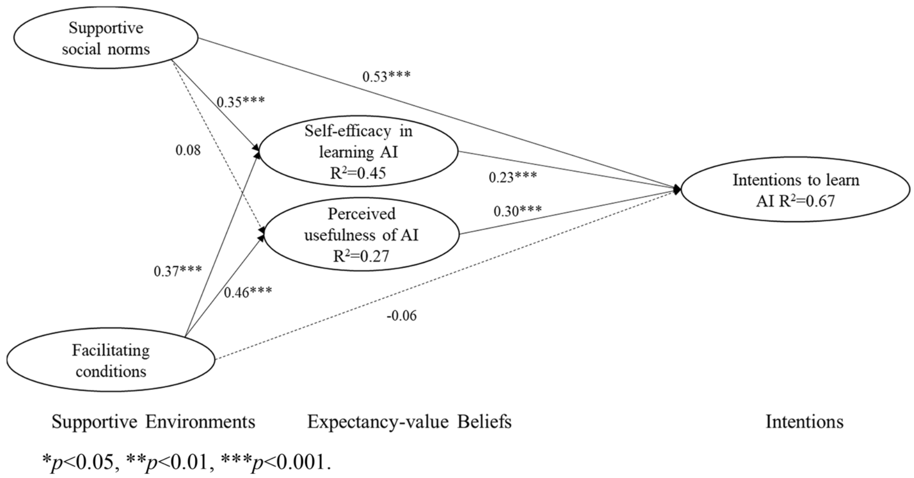

Fig. 2 Relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

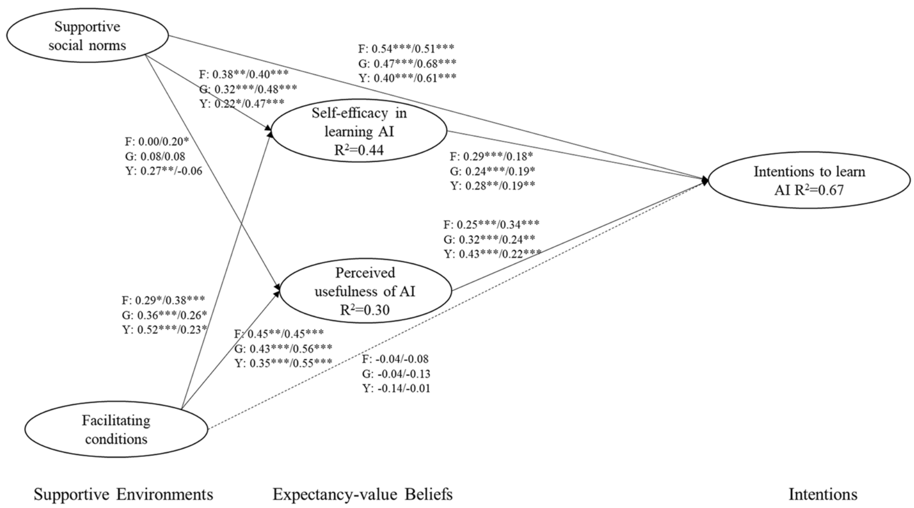

Fig. 3 Relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI across field, gender, and year. F = field of study (estimates on the left are for humanities and social sciences, and on the right are for sciences); G = gender (estimates on the left are for female, and on the right are for male); Y = year level (estimates on the left are for junior, and on the right are for senior); *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 4 Test for invariance of path coefficients across field, gender, and year

Models	χ^2	df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	*p*
Field of study									
Unconstrained model	750.02	352	0.921	0.914	0.070	0.064	11.39	8	0.18
Constrained model	761.41	360	0.920	0.916	0.070	0.077			
Gender									
Unconstrained model	879.89	352	0.902	0.894	0.078	0.063	10.35	8	0.24
Constrained model	890.24	360	0.901	0.896	0.077	0.073			
Year of study									
Unconstrained model	793.77	352	0.919	0.912	0.071	0.066	16.28	8	0.04
Constrained model	810.05	360	0.917	0.913	0.071	0.069			

Path coefficients in the unconstrained model were free to vary across groups, while path coefficients in the constrained model were constrained to equality across groups

Study 2: person-centered study

Methods

Participants and instruments

The participants and instruments in Study 2 were the same as that in Study 1.

Statistical analyses

To answer RQ3, LPA was conducted. LPA is a type of mixture modeling that assumes that the population is composed of a finite number of latent subgroups, each of which demonstrates distinct patterns of variable responses (Lubke & Muthén, 2005). In this study, we employed LPA to identify the subgroups of students (i.e., profiles) who experience different supportive environments and expectancy–value beliefs. Compared with traditional clustering analysis such as K-means clustering, LPA is more accurate because it considers measurement errors and offers a combination of goodness-of-fit indices for selecting the optimal number of profiles.

The number of latent profiles is determined through a combination of statistical criteria (Lubke & Muthén, 2005). A lower value of Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and sample size-adjusted BIC (aBIC) reflect superior model fit. Entropy higher than 0.8 indicates accurate profile classification. Meanwhile, a significant p-value of Lo-Mendel-Rubin's Likelihood ratio test (LMR) and Bootstrap Likelihood ratio test (BLRT) suggest that the K class model fits better than the K-1 class model. We also considered the theoretical interpretation and representativeness (comprising > 5% of the sample) in determining the optimal number of groups.

Furthermore, the latent profiles were used to predict intentions to learn AI. A significant value of the analysis of variance (ANOVA) test indicates that the difference in students' intentions to learn AI is significant. For RQ5, students' field of study, gender, and year level were used as predictors of latent profiles. Odds ratio (OR) is reported from this analysis, with OR greater than 1 indicating an increased likelihood of membership in a specific profile compared with the reference profile.

Results

Profile composition

As shown in Table 5, the entropy value for the three-profile solution peaked at 0.82, indicating a more accurate profile classification than other solutions. The *p*-values of LMR

Table 5 Fit indices for the models with varying numbers of latent profiles

$N_{profile}$	AIC	BIC	aBIC	Entropy	L-M-R LRT (*p*)	Bootstrap LRT (*p*)	Class size per profile
1	4569.80	4603.42	4578.02	n/a	n/a	n/a	494
2	4179.22	4233.85	4192.59	0.71	< 0.001	< 0.001	255, 239
3	**4022.45**	**4098.10**	**4040.97**	**0.82**	**< 0.001**	**< 0.001**	**42**, **278**, **174**
4	3975.52	4072.18	3999.18	0.79	0.17	< 0.001	126, 230, 20, 118

AIC Akaike Information Criterion, *BIC* Bayesian Information Criterion, *aBIC* sample-size adjusted BIC, *L-M-R LRT* Lo-Mendell-Rubin Likelihood Ratio Test, *LRT* likelihood ratio test

Bolded numbers indicated selected model

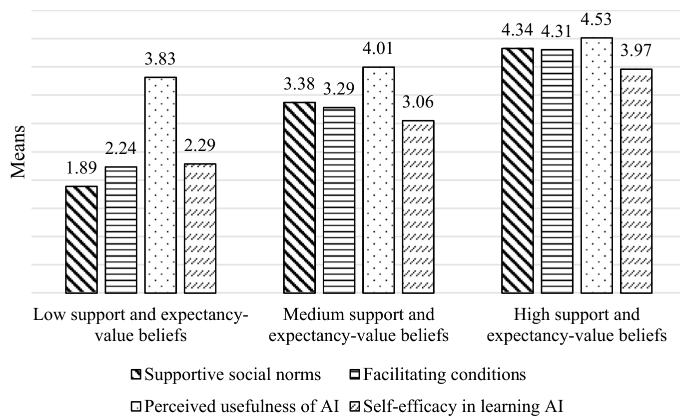

Fig. 4 Final model with the three-profile solution

Table 6 Mean differences in environmental support and expectancy–value beliefs across latent profiles

	Low support and expectancy–value beliefs ($N = 42$)	Medium support and expectancy–value beliefs ($N = 278$)	High support and expectancy–value beliefs ($N = 174$)	*ANOVA*	
	M (SE)	M (SE)	M (SE)	$F(2, 491)$	η^2
Supportive social norms	1.89 (0.14)	3.38 (0.05)	4.34 (0.07)	534.75***	0.69
Facilitating conditions	2.24 (0.16)	3.29 (0.06)	4.31 (0.06)	327.44***	0.57
Perceived usefulness of AI	3.83 (0.12)	4.01 (0.04)	4.53 (0.04)	74.30***	0.23
Self-efficacy in learning AI	2.29 (0.17)	3.06 (0.06)	3.97 (0.07)	156.92***	0.39

***$p < 0.001$

and BLRT were also significant for the three-profile solution. Moreover, the proportion of the smallest profile in the three-profile solution (n = 42) was 9%, which exceeded the cut-off value of 5%. Therefore, the three-profile solution was selected for subsequent analyses.

Figure 4 and Table 6 display the means and standard errors of the profile variables, profile names, and profile sizes. The first profile was labeled *low support and expectancy–value beliefs* (9% of participants, $n = 42$) wherein students showed the lowest levels of supportive environments and expectancy–value beliefs. The second profile was labeled *medium support and expectancy–value beliefs* (56% of participants, $n = 278$) wherein students' supportive environments and expectancy–value beliefs were at a medium level. The third profile was *high support and expectancy–value beliefs* (35% of participants, $n = 174$), with the highest levels of supportive environments and expectancy–value beliefs.

Relationship between profile membership and intentions to learn AI

We compared the mean levels of intentions to learn AI among latent profiles. The result indicated that students' intentions to learn AI across low, medium, and high support and expectancy–value beliefs were 2.77, 3.77, and 4.43, respectively, showing a significant difference ($F(2,493) = 226.24$, $p < 0.001$, $\eta^2 = 0.36$).

Table 7 The influence of field of study, gender, and year level on latent profile membership

Predictor	High vs. low OR (SE)	Medium vs. low OR (SE)	High vs. medium OR (SE)
Field of study	1.68 (0.68)	1.46 (0.58)	1.15 (0.28)
Gender	3.01 (1.28)	1.20 (0.51)	2.51 (0.61)*
Year level	0.47 (0.20)**	0.53 (0.22)*	0.93 (0.21)

Field of study: humanities and social sciences as the reference group; gender: female as the reference group; year level: junior as the reference group

OR odd ratio

*$p < 0.05$, **$p < 0.01$

Influence of field of study, gender, and year level on profile membership

As shown in Table 7, male students tended to be members of the high support and expectancy–value beliefs profile as opposed to the medium support and expectancy–value beliefs profile. Meanwhile, senior students were less likely to be in the high and medium support and expectancy–value beliefs profiles than the low profile.

Discussion

Guided by the SEVT, this study explored the relationships among supportive environments, expectancy–value beliefs, and intentions to learn AI. Overall, both the variable-centered (Study 1) and person-centered approach (Study 2) showed the critical role of supportive environments and expectancy–value beliefs in fostering students' intentions to learn AI. Study 1 indicated that expectancy–value beliefs mediated the effect of supportive environments on intentions to learn AI. Study 2 identified three subgroups of students with high, medium, and low supportive environments and expectancy–value beliefs. Two studies indicated that students with supportive environments and high levels of expectancy–value beliefs showed the strongest intentions to learn AI. Additionally, we found that demographic factors had a weak effect on supportive environments, expectancy–value beliefs, and intentions to learn AI and their relationships.

The importance of supportive environments and expectancy–value beliefs

Our study provides evidence that both supportive environments and expectancy–value beliefs are crucial factors in fostering students' intentions to learn AI, which is consistent with previous research (Kelly et al., 2023; Teo & Zhou, 2014; Venkatesh et al., 2003). First, our findings highlight the importance of creating a supportive environment that emphasizes the importance of AI and offers adequate technology resources and technical assistance to foster students' intentions to learn AI (Teo, 2010). Second, our study reveals that students who perceive higher levels of efficacy and usefulness in learning AI are more likely to learn AI. This finding is consistent with previous research, as students tend to devote more time and energy to learning activities when they have confidence in mastering and perceive important (Huang et al., 2020; Park, 2009). Third, the mediation effect of expectancy and value beliefs between supportive environments and intentions to learn AI suggests that supportive environments can enhance students' efficacy and perceived usefulness, thereby fostering their intentions to learn AI. This finding aligns with SEVT (Eccles & Wigfield, 2020) and informs universities to simultaneously focus on creating supportive environments and promoting expectancy–value beliefs to foster students' intentions to learn AI.

Our study complements previous variable-centered research by revealing individual differences in students' perceptions of supportive environments and expectancy–value beliefs in learning AI. We identified three subgroups of students that are not visible in variable-centered research (e.g., Chai et al., 2020, 2022b; Chatterjee & Bhattacharjee, 2020). The identification of low, medium, and high profiles provides a more nuanced understanding of individual differences in students' perceptions of supportive environments and expectancy–value beliefs, which can inform stakeholders to tailor interventions for the subgroups of students based on their specific needs. The majority of students in our sample (63%) fell into the low and medium profiles of supportive environments and expectancy–value beliefs, indicating that there is a huge room for improvement, especially for universities to optimize students' learning environments and foster their expectancy–value beliefs in learning AI. Specifically, the 9% of students in the low supportive environments and expectancy–value beliefs profile require particular attention to ensure that they have adequate support to develop their intentions to learn AI.

The role of demographic factors in fostering students' intentions to learn AI

Our study suggests that gender differences exist in learning AI. Both latent mean differences and LPA analysis demonstrated that male students perceive higher levels of supportive environments and expectancy–value beliefs in learning AI (Papastergiou & Solomonidou, 2005; Qazi et al., 2022; Terzis & Economides, 2011). This finding highlights the need to pay greater attention to the supportive environments and expectancy–value beliefs of female students to enhance their learning in AI. The male advantage in AI seems to corroborate prior research showing a male advantage in STEM-related subjects (e.g., Wang & Degol, 2017), but seems go against prior research showing male disadvantage in other school subjects (e.g., King & Ganotice, 2014; King, 2016; Korpershoek et al., 2021; Voyer & Voyer, 2014).

Our study shows that, compared to their senior peers, junior students were more likely to fall into the profile of high support and expectancy–value belief and were more influenced by supportive social norms (Hauk et al., 2018; Venkatesh & Davis, 2000). As individuals gain more experience with technology, the influence of significant others is expected to diminish, with individuals relying more on their own past experiences to shape their perceptions of technology, rather than the opinions of others (Venkatesh & Davis, 2000; Venkatesh & Morris, 2000). Therefore, junior students might be more sensitive to the opinions of their teachers, peers, and parents. This finding suggests that universities should focus on providing support specifically for junior students to increase their awareness of the importance of AI and foster their intentions to learn it.

Practical implications

This study has practical implications for improving students' intentions to learn AI. First, our study highlights the significance of supportive norms in promoting students' self-efficacy and intentions to learn AI. From a practical perspective, one way to create supportive norms is to offer AI-related enrichment lessons (Chai et al., 2020; Kong et al., 2021). Another route is through positive encouragement from parents, teachers, and peers (Sohn & Kwon, 2020). This finding emphasizes the importance of creating an environment that supports and encourages AI learning. Universities could consider incorporating AI-related content into the existing curriculum system (e.g., general elective courses) and offering more AI-related workshops (e.g., artificial intelligence and data science) to provide opportunities for students to enhance their experience with AI learning. Furthermore, policymakers and university leaders might need to develop clear initiatives to address the increasing importance of AI in the twenty-first century and enhance graduates' awareness of the crucial need for AI. For example, the government could publicize job reports to highlight how AI can improve employability. The university could also invite industry leaders as guest speakers to discuss the implications of AI developments in the future workplace. This is especially important in the midst of worries about the negative effects of generative AI, which could translate into restrictive policies instead of enabling ones.

Second, facilitating conditions were operationalized as the accessibility and availability of support, including technology resources and technical assistance when needed (Venkatesh et al., 2003). Our study highlights the critical role that infrastructure and resources play in supporting students' intentions to learn AI. In this context, universities could prioritize the development of AI-compatible infrastructure and provide students with access to the necessary technological resources (e.g., AI-empowered software and tools) and technical assistance. Centers for teaching and learning or academic development centers housed within universities need to upgrade the technical proficiencies of support staff to provide relevant support to university educators and students.

Third, we found that expectancy and value beliefs mediated the relationship between supportive environments and intentions to learn AI. Previous research has indicated that these beliefs are malleable and can be nurtured through appropriate interventions, such as connecting tasks to valued identities and helping students reflect on what prepares them for future success (Rosenzweig et al., 2022). To promote knowledge creation and teaching utilizing AI, higher education educators may need to intentionally learn how to apply AI into their respective specializations. This may require dedicated funding for projects that explore how to integrate AI into subject matter research, teaching, and evaluation, as well as the possible impacts of such integration. When subject matter experts consider AI as a knowledge creation and teaching tool (e.g., in the field of medicine), the integration of AI tools into the curriculum for undergraduates would become more common, establishing new norms for subject matter expertise. However, despite the potential benefits, few cross-disciplinary studies have been reported. Our study emphasizes the importance of creating a supportive learning context to foster students' motivation and expectancy beliefs in learning AI. Universities can provide students with opportunities to engage in AI-related activities that align with their values and promote confidence in their abilities by offering personalized feedback and support.

Fourth, our study indicates that female students receive less support and have lower expectancy–value beliefs than their male peers. Educators might need to create a more supportive and inclusive learning environment for female students by considering their specific needs and experiences. Meanwhile, we also found that junior students are more sensitive to social norms than their senior peers, which suggests that universities might need to set up more AI-related elective courses for junior students.

Limitations and future directions

Several limitations should be considered when interpreting the findings. First, the data used in this study were collected from self-report surveys, which might not capture the full breadth and complexity of the constructs we are measuring. We encourage future studies to collect qualitative data (e.g., interviews) to cross-validate our research findings.

Second, our data are cross-sectional, which prevents us from drawing causal and reciprocal relationships among variables. Future studies might need to gather longitudinal data to provide a more dynamic picture of how the environment and beliefs interact to promote students' intentions to learn AI.

Third, the sample of this study was drawn from Chinese mainland universities, which may limit the cross-cultural generalizability of the findings. While studies conducted in other countries, such as the UK and Belgium (Udeozor et al., 2023), Thailand (Ngampornchai & Adams, 2016), and Lebanon (Tarhini et al., 2015), have demonstrated the importance of supportive environments in influencing students' intentions to learn technologies, most of them did not specifically focus on AI. Therefore, we encourage researchers to cross-validate the generalizability of our findings in other cultural contexts. Furthermore, our study only examined university students, and future research could investigate the impact of supportive environments on AI learning among other age groups, such as primary and secondary school students.

Fourth, this study was quantitative in nature, focusing on exploring the relationship between variables rather than providing answers to "how-to" questions. Although this research paradigm has been widely used in existing technology research (e.g., Chatterjee & Bhattacharjee, 2020; Staddon, 2020), it limited our ability to identify best practices that could guide future practice. Therefore, we encourage future studies to adopt qualitative research methods, such as conducting interviews with relevant stakeholders, including government officials, teachers, and students, to better understand how these supportive environments influence students' intentions to learn AI and to identify effective strategies for promoting students' intentions to learn AI.

Fifth, although this quantitative study empirically revealed the relationship among supportive environments, expectancy and value beliefs, and students' intentions to learn AI based on the SEVT, one limitation was that all variables were predetermined based on the theoretical framework using a top-down paradigm. This approach limited our ability to gain a deeper understanding of how supportive environments influence students' intentions to learn AI, as well as explore how other elements of supportive environments influence students' intentions to learn AI. Therefore, other bottom-up exploratory methods, such as qualitative or mixed-methods designs, can be used in future studies to deepen our understanding of the relationship between supportive environments, expectancy and value beliefs, and students' intentions to learn AI using an exploratory research paradigm.

Sixth, although we provided a brief explanation of the difference between AI and non-AI and gave some examples to students before they filled out the questionnaire, it is possible that students' perceptions of supportive environments and expectancy–value beliefs may vary depending on their exposure to AI-related programs or courses. Therefore, future studies could provide a more nuanced understanding by examining the impact of different levels of exposure to AI on students' expectancy and value beliefs in learning AI, as well as the role of supportive environments in shaping these beliefs.

Last, we only examined the direct effect of supportive environments on students' expectancy and value beliefs. However, previous research by Eccles and Wigfield (2020) has suggested that learning environments may also influence these beliefs indirectly through social cognitive factors, such as personal and social identities, short-term and long-term learning goals, and affective reactions. Therefore, to gain a more comprehensive understanding of the relationship between supportive environments and expectancy–value beliefs in learning AI, future studies could explore the potential role of these mediators.

Conclusion

AI is revolutionizing the way we work and live. Hence, higher education institutions may need to further enhance students' intentions to learn AI. The variable-centered study (Study 1) demonstrated the importance of supportive environments and expectancy–value beliefs in promoting students' intentions to learn AI. Meanwhile, the person-centered study (Study 2) identified three subgroups of students based on their perceived supportive environments and expectancy–value beliefs, revealing that students who are members of the high support and expectancy–value beliefs profile tend to have greater intentions to learn AI. Males and younger students seemed have more advantages in AI learning. Students express the greatest desire to learn about AI when they are embedded in supportive environments, when they believe they can learn about AI (expectancy), and when they perceive it as useful (value). Hence, higher education institutions may need to focus on creating supportive environments and promoting students' expectancy–value beliefs to prepare them for the future workplace.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41239-023-00417-2.

Additional file 1: Appendix S1. Instruments used in this study. **Appendix S2.** Correlation matrixes of items.

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Author contributions

FW conducted the data analyses and wrote the manuscript. RBK conceptualized the study and revised the manuscript. CSC developed the questionnaire, collected data, and revised the manuscript. YZ collected data and revised the manuscript.

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Availability of data and materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Ethics approval was obtained from the Chinese University of Hong Kong.

Competing interests
On behalf of all authors, the corresponding author states that there is no conflict of interest.

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