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Understanding determinants of student behavioral intention in Singapore's AI education: insights from the situated expectancy-value theory

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ABSTRACT

Recent research in AI education has investigated motivational factors that influence students' learning intentions and experiences. However, prior studies often combined these factors into a single construct, without differentiating the multi-dimensional facets of value beliefs. Given that each dimension of task value beliefs and cost perceptions independently predicts students' performance and choices rather than a cumulative effect, the distinction could help researchers to gain a better understanding of motivation mechanism, which in turn, helps educators to design more effective and engaging AI courses that better align with students' needs and expectations. Guided by situated expectancy-value theory (SEVT) and the theory of planned behavior (TPB), this study investigated the role of supportive environment and expectancy-value-cost beliefs in shaping university students' behavioral intention in AI education. A total of 609 university students participated in this study. The findings highlighted the significant role of expectancy-value beliefs in motivating students' intention to learn and use AI. While effort cost negatively affected this intention, emotional cost positively influenced intention to acquire AI knowledge. Additionally, background factors were identified that interact with expectancy-value-cost beliefs to impact behavioral intention. This study provides both theoretical and practical implications for AI education.

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Artificial intelligence; situated expectancy-value theory; theory of planned behavior; behavioral intention; higher education

1. Introduction

Artificial Intelligence (AI) has revolutionized teaching and learning in higher education, offering new possibilities for interactive learning environments. Recent studies have highlighted several key aspects of AI's role in university settings, including AI-assisted assessment/evaluation, personalize learning experience, immediate feedback and support via intelligent tutoring systems, immersive learning through virtual and augmented reality (Crompton & Burke, 2023; Mousavinasab et al., 2021). Moreover, with the advent of generative AI technologies, students increasingly engage with AI for writing, brainstorming, research and analysis (Chan & Hu, 2023). Given the significant impact of AI on education and employment, international organizations such as the OECD (2021), UNICEF (2021), and UNESCO (Miao et al., 2021) have emphasized the importance of AI literacy and competencies for students in the twenty-first century. It is crucial for educational institutions to support and encourage students to develop AI literacy, which includes basic AI knowledge and skills for living and working with AI.

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With the growing attention to AI education, recent research investigated the motivational factors that influence students' learning intention and experiences (Chai et al., 2021, 2022; Wang et al., 2023). These findings provide valuable insights into what drives students' continuous engagement with and use of AI in learning. However, several gaps exist in previous research. First, previous research combined several motivational factors into a single construct without differentiating the multi-dimensional facets of value beliefs, particularly by not treating cost perception separately (Chai et al., 2022; Wang et al., 2023). Given that each dimension of task value beliefs and cost perceptions independently predicts students' academic outcomes rather than a cumulative effect (Jiang et al., 2018), the distinction allows researchers to gain a better understanding of motivational factors. This, in turn, enables educators to design more effective and engaging AI courses that better align with students' needs and expectations.

Second, this study investigates a diverse set of background factors that may influence students' beliefs in the AI education context, while previous research has largely overlooked these variables. These factors were identified in the theory of planned behavior (TPB) (Ajzen, 1991), including age, gender, major, prior knowledge and experience with AI applications, and exposure to AI concepts in media (Ajzen, 2011), which can provide valuable information about possible precursors of behavioral intention and individual beliefs.

Third, despite substantial investments in Singapore's AI education through initiatives like Smart Nation 2.0 (MDDI, 2024), research examining students' motivational factors within this context remains inadequate. Identifying the key factors of Singapore students' engagement with AI education could inform educational innovation strategies and contribute to the development of AI literacy skills aligned with Singapore's educational framework.

To address these shortcomings, a theoretical model that integrates two well-established frameworks: the Situated Expectancy-Value Theory (SEVT) (Eccles & Wigfield, 2020) and the Theory of Planned Behavior (TPB) (Ajzen, 1991) was proposed to understand the interrelations among supportive environments, expectancy-value-cost beliefs and students' behavioral intention in AI education, as well as the moderating role of background factors in these relationships. Specifically, two questions were answered in this research:

RQ1: How do supportive environment and expectancy-value-cost beliefs influence university students' intention to learn and use AI?

RQ2: How do background factors (i.e. age, gender, major, prior knowledge and experience with AI applications, and exposure to AI concepts in media) moderate the relationship between expectancy-value beliefs and behavioral intention in this context?

2. Literature review

2.1. Situated expectancy-value theory (SEVT)

The situated expectancy-value theory (SEVT) (see Figure 1), developed from expectancy-value theory (EVT) (Eccles, 1983), emphasizes the situated nature of expectancy-value beliefs and the interrelationship between internal motivation and external environmental factors in individual learning

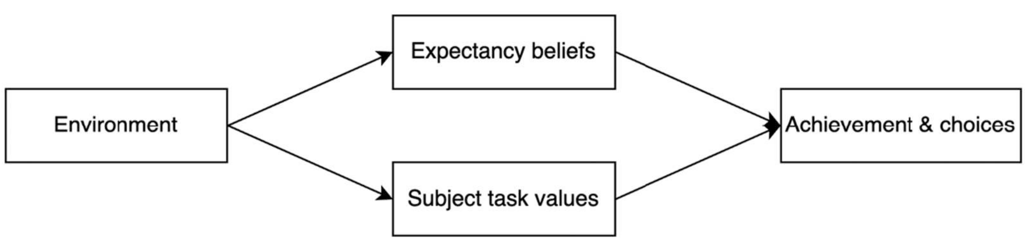

Figure 1. SEVT model.

(Eccles & Wigfield, 2020). Previous studies have found that supportive environments, such as peer support and school support, improve students' positive value perceptions while decrease students negative perceptions (Ifinedo, 2017; Rubach et al., 2023). Students who engage in peer discussions, enjoy the accessibility and availability of technology resources and technical support, and receive emotional support from schools and peers, demonstrate higher motivation and academic competence at school (Hsu et al., 2018; Wentzel et al., 2010). Therefore, this study hypothesizes that supportive environment positively predict students' motivation and individual beliefs in AI education.

In the SEVT framework, students' academic achievement and choices are driven by their expectancies for success and values they place on tasks (Eccles & Wigfield, 2020). Here, expectancy refers to a student's belief in their likelihood of success in an upcoming task (Eccles & Wigfield, 2020). In the present study, students' expectancy beliefs are operationalized as self-efficacy in learning AI (Chai et al., 2021). Subjective task values are decomposed into four components. The three positive task components are intrinsic value, attainment value, and utility value (Wigfield & Eccles, 2000). The single negative task component, termed cost, refers to individuals' anticipation of adverse outcomes from engaging in a task (Wigfield & Eccles, 2000).

Despite research on cost perception in recent years (Flake et al., 2015; Jiang et al., 2018), there remains a lack of consensus regarding the number of cost dimensions and whether cost should be integrated into task value (Eccles & Wigfield, 2020) or instead, considered as a separate construct in the Expectancy-Value-Cost Model as proposed by Barron and Hulleman (2015). Recent research examined specific dimensions of cost (i.e. effort cost, opportunity cost, and emotional cost) and found that each dimension predicts students' academic outcomes rather than a cumulative cost effect (Jiang et al., 2018). Consequently, this study treats cost as a separate construct and measure it through three dimensions (see Figure 2).

H1 and H2$_{abc}$: Peer support positively predict expectancy (AI self-efficacy) and value beliefs (a: intrinsic, b: attainment, c: utility).

H3$_{abc}$: Peer support negatively predict cost perceptions (a: effort, b: emotional, c: opportunity).

H4 and H5$_{abc}$: School support positively predict expectancy (AI self-efficacy) and value beliefs (a: intrinsic, b: attainment, c: utility).

H6$_{abc}$: School support negatively predict cost perceptions (a: effort, b: emotional, c: opportunity).

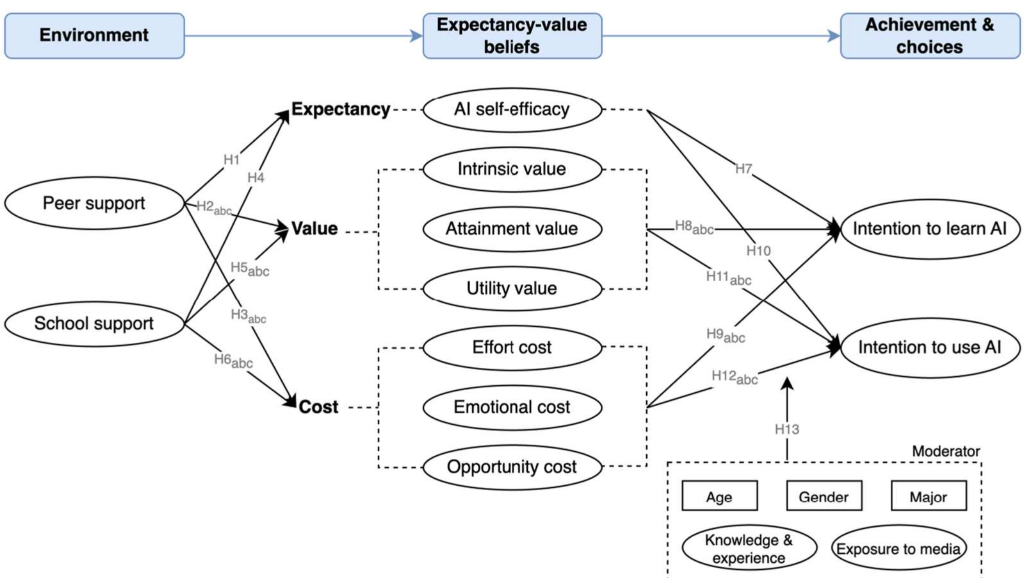

Figure 2. Proposed model.

2.2. Behavior intention in AI education

The theory of planned behavior (TPB) suggests that human behavior is determined by behavioral intention, attitudes, and subjective norms (Ajzen, 2011, 2020). Within this framework, behavioral intention is considered the most influential predictor of behavior and it determines the degree of effort and persistence individuals are willing to invest in achieving their desired outcomes (Fishbein & Ajzen, 2010). In the TPB, behavioral intention is influenced by attitude toward the behavior and social norms. Building upon the EVT and Bandura's (1977) self-efficacy concept, attitude toward the behavior is viewed as individual beliefs toward knowledge and competence for a specific task.

TPB has been extensively applied to predict behavior associated with technology applications in the educational context (Chu & Chen, 2016; Lai, 2017; Watson & Rockinson-Szapkiw, 2021). Chu and Chen (2016) demonstrated that attitudes toward the behavior, subjective norms, and perceived behavioral control accounted for more than 50% of the variance in behavioral intention to adopt e-learning. In addition, research has shown that expectancy and value beliefs are associated with positive motivational outcomes such as career choices and course enrollment decisions (Wang & Degol, 2013). Conversely, the perception of cost has been found to be related to disengagement and procrastination in a task, and the intention to quit (Jiang et al., 2018; Perez et al., 2019). Therefore, it is reasonable to hypothesize that individual beliefs (expectancy-value beliefs) are one of the determinants of behavioral intention in AI learning and AI usage. The differentiation of two types of intention is because they reflect different cognitive and behavioral orientations that students may adopt when approaching AI technologies. Intention to use AI refers to students' willingness to use AI tools as technological aids to seek information, complete tasks, or solve problems. Intention to learn AI refers to students' motivation to acquire knowledge about AI concepts, methodologies, and technical aspects (Yin & Goh, 2024).

H7 and H8$_{abc}$, H10 and H11$_{abc}$: Expectancy (AI self-efficacy) and value beliefs (a: intrinsic, b: attainment, c: utility) positively predict intention to learn and use AI.

H9$_{abc}$ and H12$_{abc}$: Cost perceptions (a: effort, b: emotional, c: opportunity) negatively predict intention to learn and use AI.

TPB also identifies a group of background factors that may influence the beliefs people hold, such as demographic variables (e.g. education, age, gender), exposure to media, and other sources of information (Ajzen, 2011). These factors provide valuable information about possible precursors of behavioral intention and individual beliefs. Research shows that *gender* moderates the effects of individual beliefs on learning intention and technology acceptance (Tarhini et al., 2014; Wang et al., 2009). *Age* also moderates the relationship between perceived value and behavioral intention in consumer studies (Molinillo et al., 2021; Moon, 2021). Furthermore, students' *major and prior knowledge* influence their intention to use mobile learning (Park et al., 2012; Zhang et al., 2017). Although less studied in education contexts, *media exposure*'s effects are widely examined in health-related and environmental contexts (Liu & Li, 2021; Yang et al., 2020).

H13: The background factors (i.e. age, gender, major, prior knowledge and experience on AI applications/knowledge, and exposure to AI concepts in media) moderate the effect of expectancy-value-cost beliefs on behavioral intention in AI education.

Based on above hypotheses, the proposed research model is shown in Figure 2.

3. Methods

Following the university's Institutional Review Board (IRB) approval,[1] each participant was given a consent form before the survey, explaining that participation was entirely voluntary, all responses would be anonymized and kept confidential, and participants could withdraw from the survey at any time without consequences. After signing the consent form, participants proceeded with the survey. Upon completion, each participant was compensated for their time and effort.

3.1. Participants

Participant recruitment was conducted through campus-wide advertisements at universities in Singapore, with QR code linking to the online survey. To ensure representativeness, the sample was stratified according to the enrollment proportions across Singapore's six major universities. A total of 609 students (mean age = 24.29, SD = 3.87) participated in this study, with most of them ($n = 494$, 81%) between 21–25 years old. There were 343 (56%) female students and 266 (44%) male students. In terms of major, 277 (45%) students were from STEM subjects such as science and engineering, and 332 (54%) students were from non-STEM subjects, such as the humanities and social sciences. This information is summarized in Table 1.

3.2. Measurement

School and peer support were adapted from Lam et al. (2010) (six items, α = .92). AI self-efficacy used four items adapted from Chai et al. (2021) (α = 0.88) to evaluate students' beliefs regarding their expectations for success in acquiring AI knowledge and utilizing AI tools. Task value consisted of three components adapted from Nagle (2021): attainment value (α = .86), utility value (α = .82), and interest value (α = .88). Cost was measured by three dimensions adapted from Robinson et al. (2019): effort cost (α = .84), emotional cost (α = .84), and opportunity cost (α = .87). Intention to learn and use AI was adapted from Teo (2011) (α = .91). Background factors consisted of three components: *Gender and major* were measured on a nominal scale. In this study, majors were categorized into STEM subjects (science and engineering, medicine) and non-STEM subjects (humanities, arts, and social sciences, business, and education). *Prior knowledge and experience* examined participants' familiarity with AI knowledge and applications; *Media exposure* was adapted from Ho's (2012) study, assessing participants' attention to AI technology across newspapers, television, and social media (α = .77−.87). The full list of survey items can be found in Appendix A.

3.3. Analysis method

Partial least squares structural equation modeling (PLS-SEM) was conducted to measure the correlation between observation variables and latent variables. First, the measurement model was evaluated by reliability, convergent and discriminant validity. Second, the structural model was constructed for path analysis. Third, the mediation effects of expectancy-value beliefs was examined. This study also analyzed how background factors moderated the relationship between expectancy-value beliefs and behavioral intention. All the above analyses were conducted using bootstrapping

Table 1. Demographic information ($N = 609$).

Variable	Category	Frequency	Percentage
Age	21–25	494	81%
	26–30	71	12%
	>30	44	7%
Gender	Female	343	56%
	Male	266	44%
Major	Science and Engineering	245	40%
	Humanities, Arts, and Social Science	191	31%
	Business (e.g. finance, accounting)	123	20%
	Medicine	32	5%
	Education	18	3%

with 5,000 subsamples and path analysis specified a 95% bias-corrected confidence interval. The R-package SEMinR in the R software was used (Hair et al., 2021).

4. Findings

4.1. Measurement model analysis

The results of the reliability, convergent validity, and discriminant validity tests are presented in Table 2. The Cronbach's alpha values ranged between 0.790 and 0.901, and Composite Reliabilities values ranged between 0.871 and 0.926. All values exceeded the critical value of 0.7. This indicates that the measurement model demonstrated reliable internal consistency. Additionally, the minimum value of Average Variance Extracted (AVE) was 0.663, higher than the 0.5 threshold, which confirmed that all constructs were well explained and correlated with each other. Furthermore, the factor loadings for each item exceeded the recommended threshold of 0.7. The discriminant validity was

Table 2. Reliability, convergent validity, and discriminant validity results.

Construct	Item	Loading	CA	CR	AVE
1. Peer Support (PS)	PS1	0.849	0.850	0.909	0.770
	PS2	0.897			
	PS3	0.885			
2. School Support (SS)	SS1	0.797	0.831	0.899	0.748
	SS2	0.911			
	SS3	0.883			
3. Self-Efficacy (SE)	SE1	0.840	0.875	0.914	0.726
	SE2	0.868			
	SE3	0.845			
	SE4	0.856			
4. Intrinsic Value (IV)	IV1	0.911	0.877	0.924	0.803
	IV2	0.918			
	IV3	0.858			
5. Attainment Value (AV)	AV1	0.844	0.877	0.925	0.804
	AV2	0.929			
	AV3	0.914			
6. Utility Value (UV)	UV1	0.881	0.875	0.923	0.800
	UV2	0.912			
	UV3	0.891			
7. Effort Cost (EFC)	EFC1	0.837	0.792	0.871	0.693
	EFC2	0.744			
	EFC3	0.908			
8. Emotional Cost (EMC)	EMC1	0.782	0.901	0.926	0.715
	EMC2	0.836			
	EMC3	0.874			
	EMC4	0.877			
	EMC5	0.855			
9. Opportunity Cost (OC)	OC1	0.895	0.879	0.925	0.805
	OC2	0.895			
	OC3	0.901			
10. Intention to Learn AI (IL)	IL1	0.805	0.842	0.894	0.679
	IL2	0.858			
	IL3	0.842			
	IL4	0.790			
11. Intention to Use AI (IU)	IU1	0.898	0.862	0.916	0.784
	IU2	0.855			
	IU3	0.902			
12. Knowledge & Experience (KE)	KE1	0.829	0.790	0.875	0.701
	KE2	0.841			
	KE3	0.841			
13. Media Exposure (ME)	ME1	0.916	0.880	0.925	0.804
	ME2	0.918			
	ME3	0.854			

Notes: CA = Cronbach's alpha, CR = Composite Reliabilities, AVE = Average Variance Extracted.

assessed by using Heterotrait–Monotrait Ratio of Correlations (HTMT) value (Henseler et al., 2015) (see Appendix B). All the HTMT values were lower than 0.85, which indicates good discriminant validity. Based on the above results, the measurement model demonstrated good reliability, convergent validity, and discriminant validity.

4.2. Structural model analysis

Figure 3 illustrates the results of the path coefficients, significance levels, and R^2 value. Peer support significantly influenced AI self-efficacy ($\beta = .423$, $p < .001$), intrinsic value ($\beta = .285$, $p < .001$), attainment value ($\beta = .215$, $p < .001$), and utility value ($\beta = .336$, $p < .001$). However, it had a negative impact on opportunity cost ($\beta = -.118$, $p < .05$). On the other hand, school support was a positive predictor for all expectancy-value beliefs, including AI self-efficacy ($\beta = .180$, $p < .001$), intrinsic value ($\beta = .159$, $p < .001$), attainment value ($\beta = .310$, $p < .001$), but not for utility value. Surprisingly, students who perceived a positive attitude toward school support exhibited higher cost perceptions in three dimensions: effort cost ($\beta = .174$, $p < .001$), emotion cost ($\beta = .141$, $p < .01$), and opportunity cost ($\beta = .115$, $p < .05$).

Regarding behavioral intention, AI self-efficacy ($\beta = .120$, $p < .05$), utility value ($\beta = .440$, $p < .001$), and effort cost ($\beta = -.135$, $p < .05$) significantly predicted students' usage intention. Intrinsic value ($\beta = .268$, $p < .001$), attainment value ($\beta = .101$, $p < .05$), utility value ($\beta = .252$, $p < .001$), and effort cost ($\beta = -.195$, $p < .001$) were significant predictors of students' learning intention. Interestingly, students who perceived higher emotional cost ($\beta = .109$, $p < .05$) exhibited greater intention for AI knowledge acquisition.

The explanatory capability of the model is also illustrated in Figure 3, where the factors account for 50.3% of intention to learn and 39.1% of intention to use. This indicates that the model possesses moderate explanatory power. In addition, f^2 was calculated to determine the effect size of exogenous variables on endogenous variables. Except for the path from peer support to self-efficacy ($f^2 = 0.211$) and from utility value to intention to use ($f^2 = 0.201$), which demonstrated medium effects, other paths exhibited small effects. This indicates that motivational factors were capable of explaining dependent variables, with a small to medium degree of explanatory effect value.

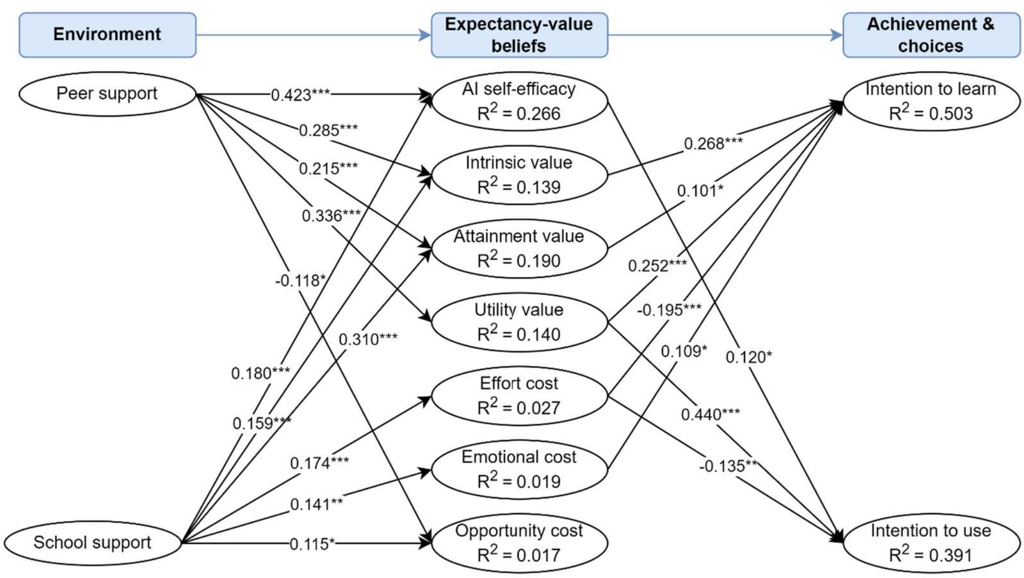

Figure 3. Path coefficients, level of significance, and R^2 value results. Notes: *$p < .05$; **$p < .01$; ***$p < .001$.

4.3. Mediation analysis

Table 3 presents the *t*-values and indirect effects of significant mediation paths. As shown in Table 3, mediation effects of intrinsic value ($\beta = .080$; $t = 3.985$; $p < .001$) and utility value ($\beta = .081$; $t = 4.930$; $p < .001$) was observed on the relationship between peer support and intention to learn AI. Moreover, self-efficacy ($\beta = .046$; $t = 2.145$; $p < .05$) and utility value ($\beta = .145$; $t = 5.750$; $p < .001$) served as mediators between peer support and intention to use AI. While a positive mediation effect of intrinsic value ($\beta = .044$; $t = 2.795$; $p < .01$) on the relationship between school support and intention to learn AI, effort cost negatively mediated the impact of school support on both intention to learn AI ($\beta = -.038$; $t = 2.890$; $p < .01$) and to use AI ($\beta = -.024$; $t = 2.104$; $p < .05$).

4.4. Moderation analysis

Table 4 lists significant moderation effects of age, gender, major, prior knowledge and experience, and media exposure on different paths. The analysis revealed a positive moderating effect of age on the relationship between intrinsic value and intention to use AI ($\beta = .097$; $t = 1.963$; $p < .05$), as well as between attainment value and intention to use AI ($\beta = .090$; $t = 2.470$; $p < .05$). This suggests that among older students, the influence of intrinsic value and attainment value on intention to use AI is more pronounced.

The moderating effect of gender was observed to positively influence the impact of self-efficacy ($\beta = .098$; $t = 1.962$; $p < .05$) and intrinsic value ($\beta = .098$; $t = 1.982$; $p < .05$) on the intention to use AI. Conversely, gender had a negative moderating effect on the impact of emotional cost on both learning intention ($\beta = -.247$; $t = -5.714$; $p < .001$) and usage intention ($\beta = -.162$; $t = -3.768$; $p < .001$). This suggests that male students perceived higher levels of self-efficacy and intrinsic value in their

Table 3. Mediation effects of paths.

Path	Indirect effect	*t*-value	*p*-value	5% CI	95% CI
PS → IV → IL	0.080	3.985	***	0.044	0.121
PS → UV → IL	0.081	4.930	***	0.052	0.118
PS → SE → IU	0.046	2.145	*	0.004	0.090
PS → UV → IU	0.145	5.750	***	0.099	0.197
SS → IV → IL	0.044	2.795	**	0.017	0.078
SS → EFC → IL	−0.038	−2.890	**	−0.064	−0.015
SS → EFC → IU	−0.024	−2.104	*	−0.049	−0.005

Notes: PS = Peer Support, SS = School Support, SE = Self-Efficacy, IV = Intrinsic Value, AV = Attainment Value, UV = Utility Value, EFC = Effort Cost, EMC = Emotional Cost, OC = Opportunity Cost, IL = Intention to Learn, IU = Intention to Use, KE = Knowledge & Experience, ME = Media Exposure.

Table 4. Moderation effects of paths.

Path	Moderation effect	*t*-value	*p*-value	5% CI	95% CI
IV*Age → IU	0.097	1.963	*	0.025	0.141
AV*Age → IU	0.090	2.470	*	0.034	0.153
SE*Gender → IU	0.098	1.962	*	0.013	0.166
IV*Gender → IU	0.098	1.982	*	0.030	0.173
EMC*Gender → IL	−0.247	−5.714	***	−0.319	−0.176
EMC*Gender → IU	−0.162	−3.768	***	−0.232	−0.091
UV*Major → IL	0.094	2.068	*	0.024	0.173
UV*Major → IU	0.092	2.037	*	0.027	0.190
SE*KE → IU	0.111	2.374	*	0.038	0.189
IV*ME → IU	0.087	1.965	*	0.020	0.164
EFC*ME → IL	0.087	1.968	*	0.026	0.173
EMC*ME → IL	−0.184	−3.118	**	−0.275	−0.086

Notes: PS = Peer Support, SS = School Support, SE = Self-Efficacy, IV = Intrinsic Value, AV = Attainment Value, UV = Utility Value, EFC = Effort Cost, EMC = Emotional Cost, OC = Opportunity Cost, IL = Intention to Learn, IU = Intention to Use, KE = Knowledge & Experience, ME = Media Exposure.

intentions to use AI compared to female students, but experienced lower emotional costs related to these intentions.

Major is another significant moderator in the relationship between utility value and intention to learn AI ($\beta = .094$; $t = 2.068$; $p < .05$) and use AI ($\beta = .092$; $t = 2.037$; $p < .05$). Here, students in STEM majors perceived a greater impact of utility value than non-STEM students. Next, prior knowledge and experience only moderated the relationship between self-efficacy and intention to use AI ($\beta = .111$; $t = 2.374$; $p < .05$). Students with more prior knowledge of and experience with AI applications perceived a greater impact of self-efficacy on their intention to use such technologies.

Finally, media exposure positively moderated the relationship between intrinsic value and intention to use AI ($\beta = .087$; $t = 1.965$; $p < .05$). Interestingly, media exposure played a moderating role that was positive between effort cost and intention to learn AI ($\beta = .087$; $t = 1.965$; $p < .05$), but negative between emotion cost and intention to learn AI ($\beta = -.184$; $t = -3.118$; $p < .01$). In other words, students who paid greater attention to AI technology in media perceived higher effort costs regarding their intention to learn AI but lower emotional costs on learning intention.

5. Discussion

5.1. The role of supportive environment and expectancy-value-cost beliefs in university students' intention to learn and use AI

First, the findings highlight the importance of peer support and school support in improving students' learning motivation and positive value perceptions, which is consistent with previous research (Rubach et al., 2023). However, contrary to the hypotheses, students who received greater school support in technological resources and technical support showed increasing perceptions of effort cost, emotional cost, and opportunity cost. This may be because integrating AI technology into courses and providing additional AI learning resources, while beneficial, requires students to invest more time and effort in applying them appropriately and effectively. Moreover, the pressure to keep up with advancements in AI technology, as well as the fear of falling behind other students who are proficient in AI knowledge, can lead to emotional stress. This is supported by prior research which found that the complexity and risk of adopting new technology may lead to technology-related anxiety among students (Blau et al., 2020; Keller & Cernerud, 2002).

Second, this study provides additional evidence that expectancy-value beliefs are key drivers in motivating students' intention to learn/use AI, which is consistent with previous research (Kelly et al., 2023). However, in contrast to previous findings suggesting that stronger self-efficacy beliefs were directly linked to greater learning intention and aspirations (Grigg et al., 2018), the results revealed no significant direct relationship between self-efficacy and learning intention. This may be because the relationship between self-efficacy and learning intention is mediated by other factors, such as self-regulation (Pihie & Bagheri, 2013) and perceived usefulness (Chang et al., 2017), as supported by previous studies. Moreover, the intrinsic value, attainment value, and utility value were all significant predictors of learning intention. This implies that individuals who perceived higher value beliefs were more likely to view the integration of AI in classrooms as exciting and beneficial. This perception, in turn, enhanced their intention to learn in the future. Hence, interventions targeting students' value beliefs can effectively promote continuous learning intention in AI education.

Third, effort cost had the most negative influence on students' behavioral intention. This aligns with prior findings where avoidance-related intentions and behaviors (e.g. disengagement and dropout) were attributed to effort cost. Particularly, Perez et al. (2014) and Foroughi et al. (2024) reported that effort cost was the most frequent cost-related response, significantly and consistently predicted STEM retention and technology usage. Surprisingly, the perception of emotional cost positively predicted intention to learn AI. This is probably because students who perceive higher emotional cost might adopt stronger mastery approach goals to maintain their self-worth. This is aligned with Jiang et al. (2018), who found that cost perception can positively predict mastery approach goals. They argued that for East Asian students, emotional cost may be closely linked to perceptions of self-worth, as these students often view academic achievement as central to their identity (Jiang et al., 2020).

Lastly, there is no significant effect of opportunity cost on behavioral intention. This is probably because opportunity cost may have both positive and negative impacts on motivation in learning. On the one hand, students who perceived opportunity cost were likely to invest more time and effort in a specific subject in order to maximize the outcomes of their choice. Similar findings were reported in Perez et al.'s (2019) study that students who perceived higher opportunity costs engaged more in learning and performed better in biology. On the other hand, the awareness of forgone opportunities can cause stress and anxiety, potentially reducing intention to learn. Previous research found that perceptions of opportunity cost may result in negative affect, leading to greater intention to leave the major (Jiang et al., 2020). Given these possibilities, the two opposing effects may occur simultaneously when students are acquiring AI knowledge and using AI applications, thus leading to no significant impact on behavioral intention.

5.2. Background factors as moderators in behavioral intention

First, the findings revealed that the effects of self-efficacy and intrinsic value on behavioral intention were more positive among male students than female students. However, the impact of emotional cost on behavioral intentions was less significant among male students than among female students. These findings highlight the necessity to pay greater attention to gender-specific interventions, for example, to enhance female students' motivation in AI learning. According to EVT, expectancy-value beliefs are shaped by gender norms and roles through socialization processes (Eccles et al., 1990). Previous findings revealed that boys developed more favorable beliefs towards traditionally male-typed domains such as science and mathematics, whereas girls developed more favorable beliefs in female-typed domains like English (Eccles et al., 1990). This has been observed in many studies, for example, Gaspard et al. (2015) found that females reported more favorable value beliefs in German, English, and biology, while males showed more preference in physics. In addition, girls perceived math as less personally important and useful for their future career choice compared to boys. Regarding cost perception, Watt (2004) found that girls perceived higher emotional cost and effort cost than boys when learning mathematics. Given that AI is often categorized as a STEM subject, it is reasonable that the influence of interest and utility value is lower, while the influence of cost perception is higher among female students in AI learning and usage.

Second, the findings revealed disciplinary differences in the relationship between expectancy-value beliefs and behavioral intention. Students who majored in STEM subjects perceived a greater effect of utility value on their intention to learn and use AI. This is probably because course material in these subjects often integrates AI knowledge and technologies and emphasizes practical applications of AI in problem-solving. As a result, students become more aware of the relevance of AI to their future careers, which enhances their motivation to engage with AI education. Conversely, students from non-STEM fields may have less exposure to AI knowledge and its practical applications, which could lead to lower perceived usefulness and subsequently reduced interest in AI-related activities. Previous studies presented similar results regarding these differences. For example, Park et al. (2012) found that major relevance was an intrinsic motivational factor that affected attitude and perceived usefulness in technology-based learning. Moreover, Thongsri et al. (2020) found that students in STEM majors had higher computer self-efficacy, perceived ease of use, and behavioral intention to use e-learning compared to their non-STEM counterparts. The findings thus indicate the need for targeted interventions to enhance non-STEM students' familiarity with and application of AI, thereby improving their motivation and learning intention in AI education.

Third, this study identified media exposure as another significant moderator. It is reasonable that students who frequently read AI-related news or stories in the media were more likely to perceive the impact of intrinsic value on their intention to use AI. This moderation effect reinforces prior research in other domains, which demonstrated that media exposure influenced the relationship between individual beliefs and behavioral intention (Jan et al., 2019; Tanski et al., 2012). Interestingly, media exposure positively influenced the relationship between effort cost and intention to learn but negatively influenced the relationship between emotional cost and intention to learn. This contrasting effect is probably due to the content of media portrayals. Positive descriptions of AI in the media can inspire students to invest more effort and time in learning. Thus, students view AI-related activities as valuable and manageable. Conversely, the overwhelming amount of information and the negative descriptions of AI technologies can cause stress or anxiety among students, thereby discouraging their learning intention. A recent study investigated how the positive and negative portrayals of AI in the news influence people's perceptions of emerging technologies (Choi, 2024). Similarly, research has shown that negative news can affect individuals' cognition (i.e. social trust) and subsequently influence their helping behaviors (Han et al., 2019). Therefore, media outlets should carefully create AI-related content in order to help students develop a proper understanding of AI technology.

6. Conclusion

Guided by SEVT and TPB, this study investigated the relationship among supportive environment, expectancy-value beliefs, and behavioral intention in AI education. The findings demonstrated the critical role of supportive environment and expectancy-value beliefs in shaping students' intention to learn and use AI. Students who perceived greater peer and school support and with higher expectancy-value beliefs showed greater intention towards AI use and knowledge acquisition. Interestingly, contrary to hypotheses, students who perceived positive school support also reported higher cost perceptions across three dimensions, implying the complex nature of these relationships. Additionally, several background factors – including age, gender, major, prior knowledge/experience, and media exposure – moderated the relationships between expectancy-value beliefs and intentions to learn and use AI. Notably, students who paid greater attention to AI technology in media perceived higher effort costs regarding their intention to learn AI but lower emotional costs on learning intention. These findings contribute a better understanding of internal and external motivational factors in shaping students' behavioral intention in AI education.

6.1. Implications

Two theoretical implications were yield. First, this study extend the SEVT (Eccles & Wigfield, 2020) and TPB (Ajzen, 1991) by using them within the theoretical framework to gain a better understanding of the mechanisms behind students' AI learning motivation and behaviors. This framework enables us to interpret, justify, and compare different motivational factors that influence behaviors, which can be applied in other technology-related contexts. The framework also demonstrates moderate explanatory power in predicting students' behaviors. Moreover, the results provide additional evidence that each dimension of cost perceptions predicts students' behavioral intention individually (Barron & Hulleman, 2015; Jiang et al., 2018). Given this, it is recommended that researchers include cost as a separate construct in the model to investigate how expectancy and value beliefs relate to academic motivation and choices.

Further, this research augment the SEVT (Eccles & Wigfield, 2020) by incorporating background factors: age, gender, major, prior knowledge/experience, and media exposure, as moderators in the context of AI education (Ajzen, 2011). The findings indicate that these factors significantly influenced individual beliefs, behavioral intention, and their relationships. These insights can guide the development of effective educational interventions and policies to engage more students in AI education.

Second, the findings contribute to motivation research in AI education by highlighting the mediating role of expectancy-value beliefs in fostering university students' intention to learn and use AI. This suggests SEVT-based intervention could effectively improve students' motivation and learning intention. Targeted interventions that focus on students' expectancies for success, value beliefs, perceived cost, and different combinations of SEVT constructs, can address the situated, synergistic, and dynamic nature of motivation factors in learning (Rosenzweig et al., 2022).

This study also provides practical implications for improving students' intention to learn and use AI. First, the findings highlight the crucial role of supportive environment in promoting students' expectancy-value beliefs and learning intention. Universities can consider undertaking strategies to reduce the perceived barriers and cost perceptions toward AI learning. For example, learning communities and online discussion forums could engage students in communication and sharing learning experiences and AI-related resources. Additionally, technology education units could be setup to support both university educators and students, particularly through workshops focused on the practical application of AI technology in study and work scenarios.

Second, the findings highlight the significance of self-efficacy, intrinsic and utility value beliefs in promoting students' behavioral intention in AI learning. To nurture these values, universities could integrate AI-related content into existing curricula at an appropriate level of coverage. These initiatives provide opportunities for students to develop their interest in AI knowledge and skills. Furthermore, policymakers and university leaders should emphasize the growing importance of AI in the twenty-first century and raise awareness about the essential role of AI skills in the future job market. Governments, for instance, could publish job analysis reports to illustrate how AI competencies and knowledge can enhance employability. Similarly, universities could invite industry experts as guest speakers to share insights on the impact of AI technology and skills in upcoming workplace environments. These efforts, in turn, could mitigate the anxiety and concerns of AI that may replace jobs.

Third, this study indicates that expectancy-value beliefs have a lesser impact on behavioral intention among female students and non-STEM students. Therefore, educators should create a more supportive and inclusive learning environment for female students and students in non-STEM majors by considering their specific needs and experiences. For example, universities could establish mentorship programs that connect female students with role models in AI and technology fields, creating women-in-technology clubs that provide resources for exploring AI knowledge and skills. This fosters a sense of belonging that encourages female students to pursue their interests and careers in AI and related disciplines. As well, universities could design interdisciplinary courses that integrate AI concepts with non-STEM subjects in order to demonstrate the relevance and application of AI across various disciplines. For example, in humanities and social science subjects, course content could cover AI applications in research, the impact of AI on these fields, and demonstrate how to leverage AI for deeper insights and analysis.

6.2. Limitations and future work

When interpreting the results of this study, several limitations need to be taken into account. First, self-reported survey data may not fully explain how various factors influence behavioral intention. To address this limitation, future research could incorporate qualitative methods (e.g. interviews) to validate and enhance the robustness of these findings. Second, the cross-sectional data prevents us from establishing causal and reciprocal relationships between variables. Future studies are recommended to collect longitudinal data to gain a more dynamic understanding of how expectancy-value beliefs influence students' intention to engage with AI learning through the passage of time. Third, the participants were recruited from local universities, which may limit the generalizability of the findings in other educational contexts such as primary and secondary schools and adult learners. Therefore, future research should aim to include a more diverse demographic both in age and geography.

Note

1. The IRB approval was obtained from (anonymous for review) University. The approval number is IRB-2023-885.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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