Expectancy-Value Beliefs as Predictors of Student Intentions in AI Learning and Application

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Abstract. Despite the growing emphasis on artificial intelligence (AI) education, there is relatively little research on the motivational factors that influence students' intention regarding AI knowledge acquisition and the utilization of AI applications. Understanding these factors not only enhances our knowledge of AI education but also helps educators and researchers to develop appropriate interventions to promote AI learning that align with students' needs and expectations. Guided by expectancy-value theory and theory of planned behavior, we investigated the role of expectancy-value beliefs in fostering university students' intentions to learn and use AI. 141 university students participated in this study. Our findings revealed that intrinsic and utility value beliefs played a mediating role in promoting students' behavioral intentions in AI learning. We also found that while effort cost negatively affected these intentions, opportunity cost positively influenced intentions to acquire AI knowledge and use AI applications. Additionally, we identified gender differences in students' expectancy-value beliefs, which can inform educators in designing gender-specific interventions to enhance female students' motivation in AI learning.

Keywords: Artificial Intelligence · expectancy-value theory · theory of planned behavior · behavioral intention · gender differences.

1 Introduction

Given the significant impact of AI on education and employment, organizations such as the OECD [1] and UNESCO [2] have highlighted the necessity for students to develop AI literacy and competencies in their recent reports. Students are now exposed to innovative AI technologies in the learning process [3]. These advanced technologies provide great potential to personalize learning experiences, give instant feedback, and facilitate learning management via intelligent tutoring systems or learning management systems [4, 5]. In the workplace, AI helps to optimize production processes, solve complex engineering and financial problems, and human resource management within organizations [6]. Recent reports estimated that AI could replace up to 300 million full-time jobs, particularly automating 46% of tasks in administrative and 44% in legal professions [7].

Therefore, it is crucial for educational institutions to support and motivate students to develop AI literacy, including understanding basic AI knowledge and how to live and work with AI.

Despite the growing emphasis on AI education, current research has predominantly concentrated on the application of AI technologies to facilitate learning [8]. Particularly, very few research investigated the factors that influence students' intentions regarding AI knowledge acquisition and the utilization of AI applications. Understanding such motivational factors provides valuable insights into what drives students' AI learning intentions. This enables researchers to further investigate and validate the multi-dimensional facets of ability and value beliefs in AI education. Consequently, educators can leverage these insights to design more effective and engaging AI courses that align with students' needs and expectations.

Expectancy-value theory (EVT) and the theory of planned behavior (TPB) are influential theoretical frameworks for understanding students' motivation and behaviors. EVT emphasizes how students' learning intentions, choices, and effort are influenced by their expectations of success, the perceived value of tasks, and their perceptions of cost [9]. TPB posits that human behavior is determined by behavioral intentions, attitudes, and subjective norms. It suggests that individual beliefs and subjective norms are the determinants of behavior intentions. Further, gender is reported to be the most significant moderator on behavioral intention and individual beliefs [10]. The TPB has been extensively applied to predict behavior associated with technology use [11, 12]. Although EVT and TPB have been applied to investigate students' learning intentions in areas like literacy [13], mathematics [14], biology [15] and physical education [16], limited research examining their impact on students' motivation and behaviors in AI education. While recent research acknowledged the critical role of motivational factors in influencing AI learning intentions [17], they combined motivational factors into a single factor without differentiating the multi-dimensional facets of value beliefs [18–20].

Therefore, guided by EVT and TPB, we investigate motivational factors that drive university students' AI use and knowledge acquisition. Specifically, we address two research questions: 1) How do expectancy-value beliefs influence university students' intention to learn and use AI? 2) What are the differences between male and female students in their motivation and behavioral intention?

2 Literature Review

2.1 Expectancy-Value Theory (EVT)

Expectancy-value theory (EVT) [21] is a leading framework in motivational psychology that focuses on the interrelation between student motivation, achievement, and achievement-related choices. According to EVT, students' academic achievement and choices are driven by their expectancies for success and values they place on tasks. Here, expectancy refers to a student's belief in their likelihood of success in an upcoming task. Expectancy beliefs are normally conceptualized as students' self-concept of ability and self-efficacy [22]. In this study, students' expectancy beliefs are operationalized as self-efficacy in learning AI.

Subjective task values are decomposed into four components [22]. The three positive task values include intrinsic value (interest and enjoyment in the task), attainment value (the task's importance for one's identity), and utility value (the task's usefulness for current or future objectives). The single negative task value, termed cost, refers to individuals' anticipation of adverse outcomes from engaging in a task. It is further divided into three components: effort cost (negative evaluations about the amount of work or the level of difficulty associated with accomplishing a task), emotional cost (the anticipated stress, anxiety, or any other negative emotional states that might result from engaging in or completing a task), and opportunity cost (the perception that other valued activities must be sacrificed in order to complete a task). Past research has shown that perceptions of positive task value are associated with positive motivational outcomes such as performance [23], career choices, and course enrolment decisions [24]. Conversely, the cost perception has been found related to disengagement and procrastination in a task and the intention to quit [15, 25].

Despite the growing research on cost perception in recent years [25–27], there remains a lack of consensus regarding the number of cost dimensions and whether cost should be integrated into task value [28] or instead, considered as a separate construct in the Expectancy-Value-Cost Model as proposed by Barron and Hulleman [29]. 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 [25]. In the light of this, we treat cost as a separate construct and measure it through three dimensions.

Regarding the interrelation among self-efficacy, task value, and cost perception, prior research indicated subject task value and cost perception served as mediators between self-efficacy and achievement/achievement-related choices [30, 31]. Students who believe they can perform a certain task are more likely to find their classes interesting, important, and useful [32]. Additionally, students with higher self-efficacy tend to perceive lower effort and emotional cost [33, 34]. Based on these findings, we hypothesize that task value and cost perception mediate the relation between self-efficacy and achievement-related choices.

2.2 Behavioral Intention in Education

The theory of planned behavior (TPB) suggests that human behavior is determined by behavioral intentions, attitudes, and subjective norms [11, 12]. Within this framework, behavioral intention is considered the most influential predictor of behavior and it determines the extent of effort and persistence people are prepared to commit in order to attain their desired results [35]. In the TPB model, behavioral intention is influenced by attitude toward the behavior and social norms. Building upon the EVT and Bandura's [21] 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 educational context [37, 38]. Chu and Chen [38] demonstrated that attitude toward the behavior, subjective norms, and perceived behavioral control accounted for more than 50% of the variance in behavioral intentions to adopt e-learning. Therefore, in this study, it is reasonable to hypothesize that individual beliefs (expectancy and value beliefs) are one of the determinants of behavioral intention in AI learning. We operationalize behavioral intention as intention to learn AI and intention to use AI.

TPB also suggests that gender may perform as a possible precursor of behavioral intention and individual beliefs [11]. Venkatesh et al. [10] found that the inclusion of gender as a moderator significantly increased the explanatory power for the acceptance of new technology. This finding is further supported by empirical research. For example, Wang et al. [39] found that gender affected the effects of performance and effort expectancy on the intention to use mobile-learning. In addition, Tarhini et al. [40] reported that gender moderated the effects of individual beliefs on behavioral intention. Similar gender differences have been observed in academic career choices [41]. The findings revealed that gender differences in attitude, subjective norm, and self-efficacy accounted for 87% of the variance in intentions to pursue academic careers between male and female students. Therefore, we argue that gender differences may exist in students' expectancy-value beliefs and behavioral intention in AI education context.

Based on the above literature review, we propose our research model as shown in Fig. 1.

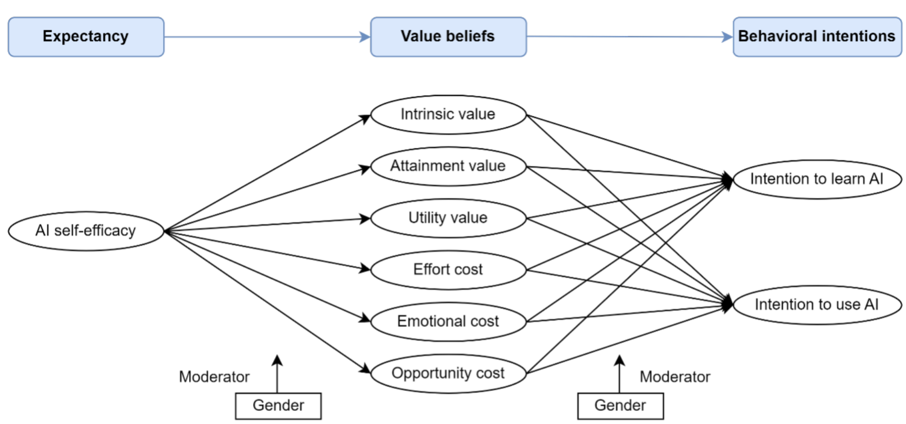

Fig. 1. Proposed research model.

3 Method

3.1 Participants

The sample in this study included 141 students ($Mean = 23.76$, $SD = 3.25$) from a local university. All participants were recruited using random sampling. There were 66 (46.8%) females and 75 (53.2%) males. In terms of major, 89 (63.1%) students were from STEM subjects such as science and engineering, and 52 (36.9%) students were from non-STEM subjects, such as humanities and social sciences. The majority of participants were full-time students (n=137, 97.2%).

3.2 Measurement

AI Self-efficacy used four items adapted from Chai et al. [19] to evaluate students' beliefs regarding their potential for success in acquiring AI knowledge and utilizing AI tools ($\alpha = 0.88$, e.g., "I feel confident that I will do well in the class involving AI applications and content.").

Task Value consisted of three components: attainment value, utility value, and intrinsic value. All the scales are adapted from Nagle [42]. The intrinsic value scale assessed students' feelings of enjoyment related to AI learning (three items, $\alpha = .86$, e.g., "AI is exciting to me"). The attainment value scale measured the importance of AI to students' identity (three items, $\alpha = .82$, e.g., "Being involved in AI is a key part of who I am"). The utility value scale measured the degree to which students found AI useful for their current or future goals (three items, $\alpha = .88$, e.g., "AI will be useful for me later in life").

Cost was measured across three dimensions: effort cost, emotional cost, and opportunity cost. All the scales were adapted from Robinson et al. [43]. Effort cost assessed students' perceptions of the amount of effort required to complete a task in AI learning (three items, $\alpha = .84$, e.g., "For me, learning AI may not be worth the effort."). Emotional cost measured students' perceptions of the negative emotional or psychological consequences of learning AI (three items, $\alpha = .84$, e.g., "I'm concerned that I am not a good enough student to do well in learning AI."). Opportunity cost measured students' perceptions of valued activities they must give up in order to learn AI (three items, $\alpha = .87$, e.g., "I'm concerned that I have to give up a lot to do well in learning AI").

Intention to learn was developed by Chai et al. [18] and has been validated among students and teachers in several studies [20, 44]. Four items were used to measure students' intention to learn AI knowledge (e.g., "I will continue to learn AI technology in the future.") and demonstrate high internal consistency ($\alpha = .91$).

Intention to use comprised three items adapted from Teo's [45] study which aimed to measure university students' intention to use AI applications in the future ($\alpha = .91$, e.g., "I intend to continue to use AI applications in the future.") This scale has been assessed in several studies, demonstrating high internal consistency with Cronbach's alpha values of .90 [46] and .94 [47].

3.3 Analysis Method

Four analytic techniques were implemented in this study. Initially, data were screened for missing values so that only complete cases were included in the analysis. The first step involved descriptive statistics and Pearson correlation analysis to gain a contextual understanding of the collected data. Second, a confirmatory factor analysis (CFA) of the proposed model was conducted to verify the factor structure of the variables. Model fit was evaluated using the following goodness-of-fit indices: Comparative fit index (CFI), Tucker–Lewis index (TLI), the root mean square error of approximation (RMSEA), and standardized root mean square error residual (SRMR). Specifically, CFI and TLI higher than 0.95 are considered a good fit and 0.90 are considered an acceptable fit, RMSEA and SRMR less than 0.08 indicate a good fit [48]. Third, structural equation modeling (SEM) was employed to analyze relationships between latent and observed variables. Fourth, multigroup CFA and structural paths comparison were conducted to identify differences between gender groups. Following the guidelines proposed by Chen [49], the criteria for metric invariance were set as, ΔCFI $\leq$ -.010, ΔRMSEA $\leq$ .015, and ΔSRMR $\leq$ .030, while the criteria for scalar invariance were ΔCFI $\leq$ -.010, ΔRMSEA $\leq$ .015, and ΔSRMR $\leq$ .010. All analyses are performed in R software with the R-package lavaan 0.6-17 [50].

4 Findings

4.1 Descriptive Statistics

Table 1 summarizes descriptive statistics, correlations, and reliabilities among observed factors. All mean scores, except for exposure to media and opportunity cost, were above the midpoint of 3.0. The items reported good internal consistency, with Cronbach values ranging from 0.81 and 0.92. All the factors exhibited positive correlations except for the relationship with cost perceptions. Specifically, prior knowledge and experience, self-efficacy, and value beliefs were positively related to intention to learn and use AI, while effort cost was negatively related to intention to learn and use AI.

4.2 Confirmatory Factor Analysis (CFA)

CFA results showed good fit, $\chi^2 = 741.39$, $p < .001$, CFI = 0.96, TLI = 0.95, RMSEA = 0.05 (95% CI = [0.04, 0.06]), SRMR = 0.05. All the standardized factor loadings were significant ($p < .001$) and exceeded the recommended minimal value of 0.5 [51], which demonstrated good convergent validity of the measurement scales. In addition, the average variance extracted (AVE) exceeded the value of 0.50, which indicated good discriminant validity across all constructs.

4.3 Structural Equation Modeling (SEM)

Based on the CFA results, we constructed a structural model. The model demonstrated a satisfactory fit with CFI = 0.95, TLI = 0.95, RMSEA = 0.06 (95% CI

Table 1. Descriptive statistics, correlations, and reliabilities among variables (N= 141. *$p < .05$; **$p < .01$; ***$p < .001$).

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1. Knowledge & experience	—										
2. Exposure to media	0.499***	—									
3. Self-efficacy	0.438***	0.394***	—								
4. Intrinsic value	0.339***	0.391***	0.618***	—							
5. Attainment value	0.290***	0.436**	0.533***	0.713***	—						
6. Utility value	0.254**	0.246**	0.493***	0.667***	0.487***	—					
7. Effort cost	-0.084	0.151	-0.072	-0.103	0.062	-0.070	—				
8. Emotional cost	-0.053	0.102	-0.244*	-0.112	0.173*	-0.120	0.484***	—			
9. Opportunity cost	0.015	0.155	-0.125	-0.124	0.153	-0.170*	0.533***	0.755***	—		
10. Intention to learn AI	0.351***	0.355***	0.395***	0.566***	0.458***	0.496***	-0.201*	-0.012	0.224*	—	
11. Intention to use AI	0.266**	0.246**	0.308***	0.456***	0.431***	0.492***	-0.202*	-0.002	0.204*	0.719***	—
Mean	3.16	2.93	3.72	3.64	3.36	4.13	3.07	3.11	2.85	3.91	4.15
SD	0.86	0.77	0.69	0.86	0.98	0.71	0.90	1.01	1.01	0.58	0.58
Cronbach's α	0.81	0.83	0.86	0.89	0.89	0.91	0.83	0.92	0.89	0.83	0.88

= [0.04, 0.06]), and SRMR = 0.07. To better present the relationships among expectancy-value beliefs, and intention to learn and use AI, Fig. 2 depicted path coefficients and their corresponding level of significance. As shown in Figure 2, AI self-efficacy significantly influenced intrinsic value ($\beta = .722$, $p < .001$), attainment value ($\beta = .604$, $p < .001$), and utility value ($\beta = .541$, $p < .001$). However, AI self-efficacy only significantly predicted emotional cost ($\beta = -.261$, $p < .05$). Students' intrinsic value ($\beta = .510$, $p < .01$) positively explained their intentions to learn AI. Furthermore, their utility value beliefs positively predicted both intentions to learn ($\beta = .268$, $p < .05$) and use AI ($\beta = .399$, $p < .01$), while the perception of effort cost negatively influenced their intentions to learn ($\beta = -.304$, $p < .01$) and use AI ($\beta = -.276$, $p < 0.01$). Interestingly, students who perceived higher opportunity cost demonstrated greater behavioral intention to acquire AI knowledge ($\beta = .384$, $p < .05$) and use AI applications ($\beta = .273$, $p < .05$).

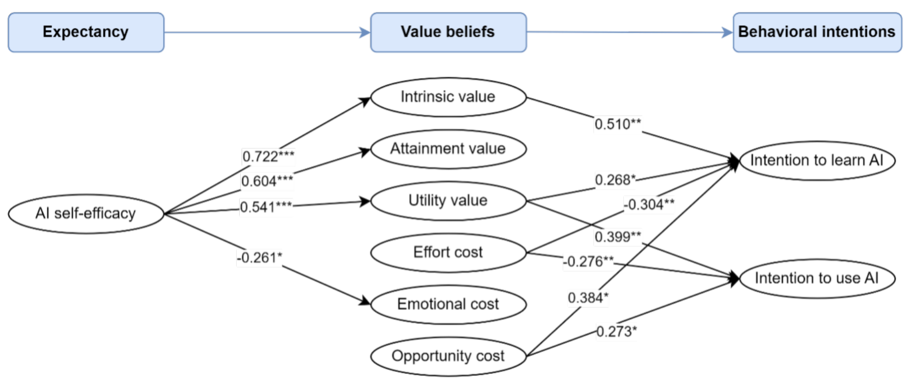

Fig. 2. SEM Path analysis results.

Table 2 presents the indirect effects and the total effects of AI self-efficacy on intention to learn and use AI. We observed that intrinsic value significantly mediated the relationship between self-efficacy and intention to learn ($\beta = .368$, 95% CI [0.02, 0.50], $p < .01$) and use AI ($\beta = .111$, 95% CI [0.03, 0.23], $p < .05$). Utility value also played a mediating role between self-efficacy and intention to learn ($\beta = .145$, 95% CI [0.02, 0.21], $p < .05$) and use AI ($\beta = .216$, 95% CI [0.05, 0.26], $p < .01$. Furthermore, we observed that the indirect effect ($\beta = .556$, 95% CI [0.10, 0.39], $p < .001$ and the total effect ($\beta = .646$, 95% CI [0.17, 0.45], $p < .001$ of AI self-efficacy on intention to learn AI knowledge were significant. Similarly, the indirect effect ($\beta = .435$, 95% CI [0.15, 0.27], $p < .001$ and the total effect ($\beta = .525$, 95% CI [0.25, 0.59], $p < .001$ of AI self-efficacy on intention to use AI applications were significant as well.

Table 2. Mediation analysis results (*$p < .05$; **$p < .01$; ***$p < .001$).

Outcome	Mediator	Estimate	95% CI
Intention to learn AI	Intrinsic value	0.368**	[0.02, 0.50]
	Attainment value	0.034	[-0.16, 0.21]
	Utility value	0.145*	[0.02, 0.21]
	Effort cost	0.021	[-0.05, 0.04]
	Emotional cost	0.038	[-0.02, 0.04]
	Opportunity cost	-0.050	[-0.09, 0.03]
	Total indirect effect	0.556***	[0.10, 0.39]
	Total effect	0.646***	[0.17, 0.45]
Intention to use AI	Intrinsic value	0.111*	[0.03, 0.23]
	Attainment value	0.109	[-0.08, 0.24]
	Utility value	0.216**	[0.05, 0.26]
	Effort cost	0.019	[-0.04, 0.03]
	Emotional cost	0.016	[-0.02, 0.01]
	Opportunity cost	-0.036	[-0.06, 0.02]
	Total indirect effect	0.435***	[0.15, 0.27]
	Total effect	0.525***	[0.25, 0.59]

4.4 Multigroup SEM

First, we evaluated measurement invariance. The configural model had an acceptable fit across gender groups (CFI = 0.94; RMSEA = 0.06, SRMR = 0.07). Next, we constrained factor loadings and intercepts to establish metric and scalar invariance (as shown in Table 3). The scalar model showed a poor fit and the changes in CFI and SRMR both exceed thresholds. Thus, we were only allowed to compare structural paths between groups instead of factor means.

Table 3. Test for invariance across gender groups.

Groups	Models	CFI	RMSEA	SRMR	ΔCFI	ΔRMSEA	ΔSRMR
Gender	Baseline	0.95	0.06	0.07			
	Configural	0.94	0.06	0.07	-0.01	0.00	0.01
	Metric	0.93	0.07	0.08	-0.01	0.01	0.02
	Scalar	0.90	0.08	0.13	-0.02	0.01	0.04

We estimated a metric-invariant model in which the structural paths were constrained to equality between gender groups. Regarding intention to learn AI knowledge, the analysis results revealed that 1) the relationship between self-efficacy and utility value belief was more positive in males (β = 0.79) than in females (β = 0.67), $\Delta\beta$ = .12, $p < .01$, 2) the relationship between self-efficacy and effort cost was more negative in females ($\beta = -0.89$) than in males ($\beta = -0.13$), $\Delta\beta = -0.77$, $p < .01$, and 3) the relationship between self-efficacy and emotional cost was more negative in females ($\beta = -0.30$) than in males ($\beta = -0.07$), $\Delta\beta = -0.23$, $p < .05$.

Regarding intention to use AI applications, the results revealed that 1) the relationship between self-efficacy and attainment value belief was more positive in males ($\beta = 0.80$) than in females ($\beta = 0.60$), $\Delta\beta = 0.20$, $p < .05$, 2) the relationship between self-efficacy and utility value belief was more positive in males ($\beta = 0.78$) than in females ($\beta = 0.60$), $\Delta\beta = 0.18$, $p < .001$, 3) the relationship between self-efficacy and effort cost was more negative in females ($\beta = -0.36$) than in males ($\beta = -0.15$), $\Delta\beta = -0.21$, $p < .05$, and 4) the relationship between self-efficacy and emotional cost was more negative in females ($\beta = -0.49$) than in males ($\beta = -0.08$), $\Delta\beta = -0.41$, $p < .05$.

5 Discussion

Guided by EVT and TPB, this study examined the relationship between expectancy-value beliefs and behavioral intentions in AI education. The findings underscored the significant influence of expectancy-value beliefs on shaping students' intentions to learn and utilize AI. Results revealed that students with higher levels of self-efficacy and value beliefs demonstrated a stronger intention to engage with and apply AI. Additionally, the study identified gender-influenced expectancy-value beliefs, as well as behavioral intentions and their relationships.

5.1 Value Beliefs in Behavioral Intentions

Our study supports the significance of value beliefs as key drivers in motivating students' intention to learn and use AI, consistent with previous research [17]. First, students who perceive higher levels of utility value beliefs are more preferring to learn AI knowledge and apply AI applications. Previous research also suggested that students who perceived higher utility value tend to have better performance and positive learning behavior [52].

Second, although attainment value was not a significant predictor in this study, it may play a moderating role in the relationship between expectancy beliefs and behavioral intentions. Bivariate correlation analysis showed that attainment value positively correlated with intention to learn and use AI. However, the structural model indicated that, after controlling for other beliefs, attainment value did not significantly contribute additional variance to behavioral intentions. This suggests that the role of attainment value may potentially influence the relationship between expectancy beliefs and intentions as a moderating role instead of a direct prediction. This has been reported in two studies where the interaction between expectancy and attainment value significantly impacted English academic achievement [53, 60].

Third, we only observed the mediation effects of intrinsic value and utility value between self-efficacy and intention to learn and use AI. This finding suggests that when individuals perceive themselves as competent to learn and use AI, they are more likely to find the integration of AI in classrooms is exciting and beneficial. This perception, in turn, enhances their intention to learn and use AI in the future. Hence, enhancing perceived interest and utility for current or future goals can effectively foster students' intention to learn and use AI. The results provide additional evidence that enhancing students' utility value serve as an effective intervention to improve learning achievement and behaviors [54].

5.2 Perceived Cost in Behavior Intentions

First, we found that effort cost has the most negative influence on students' behavioral intention. Aligned with prior findings, the avoidance-related intentions and behaviors (e.g., disengagement and dropout) are attributed to effort cost [26, 27, 55]. Particularly, Perez et al. [27] and Flake et al. [26] demonstrated that effort cost was the most frequent cost-related response (42%), and significantly and consistently predicted the intention to leave from STEM majors over time.

Surprisingly, the perception of opportunity cost positively predicted intention to learn and use AI. Prior research also revealed conflicting results regarding the role of opportunity cost in achievement and behaviors. For example, Fries and Dietz [56] found that increasing high school students' perceptions of opportunity cost had detrimental effects on their performance. In contrast, Perez et al. [15] observed a positive relation between opportunity cost and final biology grades. This is probably because individuals' perceptions of opportunity costs are offset by their awareness of the potential benefits they anticipate from engaging with AI learning and technologies. Such awareness might motivate them to invest time and effort into learning and utilizing AI, viewing it as a strategic investment in their personal or professional growth.

Third, we did not observe a significant effect of emotional cost on behavior intention. Several reasons could explain this result. First, rather than emotional cost directly affecting behavioral intention in the context of our study, it might be mediated or moderated by other variables, such as perceived ease of use and perceived usefulness of AI technology [57]. Similar findings have been reported in previous studies that the effect of emotional cost on behavioral intention were mediated by perceived ease of use and perceived usefulness of new technology [58, 59]. Second, emotional cost may have both positive and negative impacts on motivation in learning. On the one hand, anxiety about AI job replacement may have positive influence on students' learning motivations [60]. On the other hand, anxiety toward AI learning could negatively affect motivations, leading to avoidance attitudes and behaviors toward computers and technology [61]. These two effects may occur simultaneously when students are acquiring AI knowledge and using AI applications.

5.3 Gender Differences Intention to Learn and Use AI

The results imply that gender differences exist in relationships between expectancy-value beliefs and AI use and knowledge acquisition. The results revealed that the relationship between value beliefs and behavioral intentions is more positive among male students than female students. Conversely, the relationship between cost perceptions and behavioral intention is lower among male students than among female students. This finding highlights the necessity to pay greater attention to gender-specific interventions to enhance female students' motivation in AI learning.

According to EVT, expectancy and value beliefs are shaped by gender norms and roles through socialization processes [62]. Researchers argued that boys develop more favorable beliefs towards traditionally male-typed domains such as science and mathematics, whereas girls develop more favorable beliefs in female-typed domains like English [62]. This has been observed in many studies, for example, Gaspard et al. [63] 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 [64] 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.

6 Conclusion

Our study complements previous AI education research by investigating the impact of students' perceptions of expectancy-value beliefs and cost perceptions on behavioral intentions in AI learning and usage. The findings provide a more nuanced understanding of multi-faceted motivational factors in shaping students' behavioral intentions in AI education.

6.1 Implications

This study provides two theoretical implications. First, we applied EVT and TPB as theoretical framework to gain a better understanding of the mechanisms behind students' AI learning motivation and behaviors. Our proposed model enables researchers to interpret, justify, and compare the multi-faceted motivational factors that influence behavioral intention. Notably, our findings provide additional evidence that each dimension of cost perceptions predict students' behavior intentions individually. This model shows potential to be applied in other technology-related contexts. Second, our findings contribute to motivation research in AI education by highlighting the mediating role of intrinsic and utility value beliefs in motivating university students' intention to acquire AI knowledge and apply AI applications. Further, the observed gender differences provide evidence of gender acting as a moderator in the relationship between individual beliefs and behavioral intention. These insights can guide the development of effective educational interventions and policies to engage more students in AI education.

This study also provides practical suggestions for motivating students in AI education. First, our study emphasizes the role of intrinsic and utility value beliefs in promoting students' behavioral intentions in AI learning. To nurture these values, universities could integrate AI-related content into existing curricula and offer more AI-related workshops. 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 21st 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 alumni to share working experience 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. Second, to cultivate students' value beliefs and encourage a positive engagement with AI technology, educators need to familiarize themselves with applying AI in research, teaching, and evaluation. They also need to understand the potential risks and benefits of AI integration in guiding and supporting students. Third, our study indicates that expectancy-value beliefs have a lesser impact on behavioral intentions among female students compared to their male peers. Therefore, schools and institutions should foster a more supportive and inclusive learning environment for female students by taking into account their preferences and needs. 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 and encourages female students to pursue their interests and careers in AI and related disciplines.

6.2 Limitations and Future Work

When interpreting the results of our study, several limitations need to be taken into account. First, self-reported survey data may not fully explain how various factors influence behavioral intentions. To address this limitation, we recommend future research to 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' intentions to engage with AI learning. Third, our participants were recruited from a local university, which may limit the generalizability of the findings in other contexts. Therefore, future research should aim to include a more diverse demographic, such as younger students from primary and secondary schools.

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