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MORE THAN SKILLS: HOW AI LITERACY SHAPES STUDENT MOTIVATION IN THE AGE OF EDUCATION 4.0

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Abstract

Grounded in Expectancy-Value Theory (EVT), this study examined the relationship between students' AI literacy and their motivation to use AI in academic contexts. Specifically, it explored how four AI literacy domains, namely awareness, usage, evaluation, and ethics, relate to expectancy beliefs and task value components (attainment, utility, intrinsic/interest, and cost). Data were collected from Filipino college students enrolled in a general education science course and analyzed using descriptive statistics, t-tests, ANOVA, correlation, and multiple regression. Results showed that students possessed high AI literacy across all domains, with the highest rating in awareness. Motivation was generally high across task value components but moderate for expectancy beliefs and cost. Female students demonstrated slightly higher intrinsic motivation, evaluative skills, and ethical awareness than males, while no significant differences were observed across academic programs. Correlation analyses revealed small-to-moderate relationships between AI literacy and motivational beliefs, except for the non-significant link between ethics and utility values. Among the literacy domains, usage exhibited the strongest associations and emerged as the only significant predictor of task value components, highlighting the motivational benefits of hands-on AI engagement. Although AI literacy accounted for a small proportion of variance in motivation, the findings emphasize its meaningful role in fostering students' confidence, value perceptions, and ethical reflection. The study underscores the importance of experiential, reflective, and inclusive AI learning approaches that cultivate both competence and sustained motivation in higher education.

Keywords – AI literacy, Motivational beliefs, Expectancy-value theory, Higher education.

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1. Introduction

Artificial Intelligence (AI) is continuously shaping various sectors, including education. With the emergence of Education 4.0, AI plays a key role in transforming the learning process by supporting adaptive, self-directed, and immersive learning (Rane, 2024; Lata & Kumari, 2025). Education 4.0 aims to equip learners with the required skills to successfully adapt in an increasingly digitalized and globalized world through personalized, flexible, and technology-integrated learning environments (Portilla, 2025). However, effective engagement with AI requires not only technical skills but also the motivation to willingly use them meaningfully, responsibly, and independently. In this case, motivation is the students' belief in their competence and the value they see in using AI (Wigfield & Eccles, 2000). Students who can confidently use AI tools (expectancy) and believe they are important and enjoyable (task value) are more likely to embrace AI positively (Yin & Goh, 2024). These motivational beliefs are often shaped by students' knowledge and skills, notably their AI literacy (Zhao, 2025).

While commonly viewed as a set of technical skills, AI literacy is a multidimensional concept. It encompasses four domains, which include (1) awareness of AI capabilities, (2) actual usage of AI tools, (3) ability to assess AI-generated content critically, and (4) understanding of the ethical implications of AI in both academic and social settings (Ng, Leung, Chu & Qiao, 2021; Ma & Chen, 2024). These domains are aligned to the broader objective of Education 4.0, which is to develop digital citizens who are reflective, adaptive, and ethically informed (Costa, Cangussu, Gonçalo, Reinoso, Lemos, Azevedo et al., 2025). As such, AI literacy may play a critical role in shaping students' motivation to use AI by boosting their confidence, clarifying its relevance to academic success, and reducing apprehensions or perceived barriers (Chiu, Ahmad, Ismailov & Sanusi, 2024).

Despite the growing focus of AI research in education, there are still few studies on AI literacy. Many previous works have focused on digital literacy, which appears to be similar to AI literacy (Siddiq, Gochyyev & Wilson, 2017; Ghomi & Redecker, 2019; Li & Hu, 2020). Wang, Rau and Yuan (2022) pointed out, however, that digital literacy is not a replacement for AI literacy, since this is an interdisciplinary field. This distinction underscores the need for independent research on AI literacy (Ma & Chen, 2024). Moreover, existing AI literacy frameworks (Wang et al., 2022; Laupichler, Aster, Haverkamp & Raupach, 2023) also failed to survey college students in developing countries. Furthermore, AI research in developing countries is more focused on technical proficiency, knowledge, and frequency of use, rather than on psychological and emotional factors that stimulate AI use (Wulyani, Widiati, Muniroh, Rachmadhany, Nurlaila, Hanifiyah et al., 2024; Saihi, Ben-Daya & Hariga, 2024; Rahman, Hossain, Ismail, Hossen & Sultana, 2025; Rosa, Dacuma, Ang, Nudalo, Cruz & Vallespin, 2024).

Hence, the current study aims to investigate the relationship between students' AI literacy and their motivation to utilize AI. Understanding their relationship is crucial for creating learning experiences and institutional supports that foster both digital competencies and meaningful engagement with AI in the Education 4.0 era. This study primarily examines the influence of students' four AI literacy domains — awareness, usage, evaluation, and ethics — on their five motivational constructs, as conceptualized within the Expectancy-Value Theory (EVT) (Yurt & Kasarci, 2024). Expectancy pertains to individuals' beliefs in their ability to effectively execute a specific work, while value reflects the perceived significance and benefits of that task to the individuals (Yurt & Kasarci, 2024). There are four value subcomponents: attainment, utility, intrinsic or interest, and cost values. Attainment values refer to the personal significance of a task, particularly when it aligns with one's identity (Eccles & Wigfield, 2002). Utility value is described as the task's relevance to future goals (Barron & Hulleman, 2015), whereas intrinsic value reflects the satisfaction or interest gained from a task (Ryan & Deci, 2000). The cost includes the perceived effort, the danger of failure, and the trade-offs associated with task completion (Barron & Hulleman, 2015). Understanding these motivating factors helps explain why people engage with AI tools and technologies.

In addition to EVT as the main theoretical framework of the study, the theories Social Cognitive Theory (SCT), Self-Determination Theory (SDT), and Technology Acceptance Model (TAM) were also applied to provide a more comprehensive understanding of the interplay between AI literacy and motives for using AI. The SCT emphasizes the influence of personal factors, behavioral patterns, and environmental influences on learning and motivation (Bandura, 1997). Self-efficacy, which is a component of SCT, refers to an individual's confidence in their ability to accomplish a task. This is an essential factor in their motivation, decision-making skills, and persistence to learn new technologies. SDT emphasizes the importance of addressing fundamental psychological needs, such as competence, autonomy, and relatedness, to foster growth (Ryan & Deci, 2000). Finally, the TAM shows that perceived usefulness and ease of use are essential factors in shaping technology adoption (Davis, 1989). Based on this multi-theoretical perspective and multiple regression analysis, the study aims to advance understanding of the psychological predictors of students' motivation to use AI in higher education. The results aim to inform educators, curriculum developers, and instructional leaders in guiding interventions that foster not only the technical form, but also the motivational readiness, ethical sensitivity, and self-directed engagement – critical tenets of Education 4.0.

Generally, this study aims to investigate the relationship between students' AI literacy and their motivations for using AI tools. Specifically, this study has the following objectives:

1. To describe the levels of AI literacy and motivational beliefs (expectancy, attainment value, utility value, intrinsic/interest value, and cost) among college students;
2. To determine whether significant differences exist in AI literacy and motivational beliefs when grouped by sex and academic program;
3. To assess the relationships between the four dimensions of AI literacy (awareness, usage, evaluation, and ethics) and students' motivational beliefs; and
4. To evaluate the predictive power of AI literacy dimensions in determining students' motivational beliefs using multiple regression analysis.

2. Methodology

2.1. Research Design

A quantitative correlational research design with inferential statistics was utilized to investigate the predictive correlations between students' AI literacy and motivational beliefs. The research was conducted in a higher education setting, specifically among college students enrolled in the general education course Science, Technology, and Society.

2.2. Participants of the Study

The participants in this study were selected using stratified random sampling to ensure academic representation among three programs that offered the General Education course Science, Technology, and Society (GE 7) during the second semester of the academic year, 2024-2025. A priori power analysis was performed using G*Power 3.1.9.7 to calculate the required sample size for multiple linear regression with four predictors. Based on a medium effect size ($f^2 = 0.15$), an alpha level of 0.05, and a desired power of 0.90, a minimum of 108 participants is required to detect a statistically significant effect. The sample size of 150 participants exceeded this requirement, indicating that the study was sufficiently powered to detect meaningful effects and reduce the likelihood of Type II errors (Erdfelder, Faul & Buchner, 1996).

2.3. Research Instrument

The online survey instrument consisted of four parts. Part I outlined the purpose of the study and the informed consent obtained in accordance with the Data Privacy Act. Part II collected demographic information, including respondents' sex and academic program. Part III contained items from the AI Literacy Scale (ALS) (Ma & Chen, 2024) which included four constructs: Awareness, Usage, Evaluation and Ethics; and Part IV featured the Questionnaire of AI Use Motives (QAIUM) by Yurt and Kasarci (2024) grounded in the Expectancy-Value Theory (Wigfield & Eccles, 2000) covering five constructs: Expectancy and Task Value encompassing Attainment;, Utility, Intrinsic/interest value and Cost. Items were rated using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree) for the ALS, and from 1 (completely false) to 5 (completely true) for the QAIUM.

Both adopted instruments underwent pilot testing to verify their reliability and suitability within the study context and Confirmatory Factor Analyses (CFA) to establish construct validity. Cronbach's alpha values showed excellent internal consistencies (ALS = 0.945; QAIUM = 0.974). The CFA, on the other hand, yielded acceptable model fit indices for the ALS: χ^2 (df = 84) = 211, $\chi^2/df = 2.51$, $p < .001$;

SRMR = 0.045; CFI = 0.928; IFI = 0.929; GFI = 0.962; AGFI = 0.940, and for the QAIUM: χ^2 (df = 160) = 413, χ^2/df = 2.58, $p < .001$; SRMR = 0.048; CFI = 0.906; IFI = 0.907; GFI = 0.987; AGFI = 0.982. These indices met the recommended standards (χ^2/df = 1–3; CFI, IFI, GFI, AGFI $\geq$ 0.90; SRMR $\leq$ 0.08) (Hu & Bentler, 1999), which showed that the measurement models were good enough. The results aligned with those presented by the original developers, who similarly identified acceptable construct validity and model fit indices (e.g., RMSEA < 0.08, CFI > 0.90) (Ma & Chen, 2024; Yurt & Kasarci, 2024).

2.4. Data Gathering Procedure

A web-based survey was developed using Google Forms and distributed through the official group chats of each class. Data were collected during the second semester of the academic year 2024-2025. The study adhered to the institution's ethical standards and formal permission was obtained from the relevant offices before data gathering. Before answering the questionnaire, participants were provided with an electronic informed consent form that explained the purpose of the study. Participation was voluntary and confidentiality was strictly maintained.

2.5. Data Analysis

Data were analyzed using Jamovi software. Descriptive statistics (frequency, percentage, mean, and standard deviation) were used to summarize students' levels of AI literacy and motivation. Group differences based on sex and academic program were examined using independent samples t-tests and one-way ANOVA. Pearson's r correlation was employed to assess the relationships between AI literacy and students' motivational beliefs. To assess the predictive power of the four AI literacy dimensions) on expectancy and task value components, multiple linear regression analyses were conducted. All statistical tests were performed at a significance level of $\alpha = 0.05$, with relevant assumptions checked before analysis.

3. Findings

This section presents the results of the analyses conducted to address the research objectives. The respondents of the study were students enrolled in the General Education course Science, Technology, and Society (GE 7) during the second semester of the academic year 2024–2025. They came from three academic programs: Bachelor of Elementary Education (BEED), Bachelor of Science in Tourism Management (BSTM), and Bachelor of Science in Hospitality Management (BSHM). The findings highlight the respondents' levels of AI literacy and motivational beliefs, as well as the relationships and predictive paths among the study variables.

Table 1 presents the demographic profile of the respondents. As shown in the table, the majority of the participants were female (66.67%). In terms of academic program, most of the respondents were enrolled in the Bachelor of Science in Hospitality Management (BSHM), comprising 45.33% of the total sample. The remaining participants were equally distributed between the Bachelor of Elementary Education (BEEd) and the Bachelor of Science in Tourism Management (BSTM), each representing 27.33% of the respondents.

Variables	f	%
Gender		
Male	50	33.33
Female	100	66.67
Program		
Bachelor of Elementary Education (BEEd)	41	27.33
Bachelor of Science in Tourism Management (BSTM)	41	27.33
Bachelor of Science in Hospitality Management (BSHM)	68	45.33
Total	150	100.0

Table 1. Demographic profile of respondents

3.1. Descriptive Statistics

3.1.1. Students' Level of AI Literacy

Table 2 reveals that the students demonstrated a high overall level of AI literacy (M = 3.56, SD = 0.75) with the highest mean score in Awareness (M = 3.61, SD = 0.87). This reflects strong familiarity with general AI ideas, likely due to frequent exposure to AI-powered technologies and the increasing presence of AI in media and education (Sova, Tudor, Tartavulea & Dieaconescu, 2024; Farrokhnia, Banihashem, Noroozi & Wals, 2023; Hasanein & Sobaih, 2023). Similarly, high literacies were observed under Usage (M = 3.54, SD = 0.84), Evaluation (M = 3.58, SD = 0.80), and Ethics (M = 3.50, SD = 0.78).

Their high AI usage suggests their effectiveness in integrating AI into learning tasks such as research writing, problem-solving, and other academic-related tasks. This meaningful use of AI tools can be attributed to students' positive perceptions of their usefulness and ease of use (Davis, 1989), as well as their increasing incorporation into educational settings (Nikoulina & Caroni, 2024; Hermosura, 2025; Zaidy, 2024; Zhou, Zhang & Chan, 2024; Sova et al., 2024). Frequent interactions with AI can also promote ethical reflection and critical comprehension (Wang, Chai, Li & Lee, 2025). This explains the observed high scores of the students in the Evaluation and Ethics domains.

Items on AI Literacy		Mean	SD	Description
Awareness	Understands AI definition	3.91	1.07	High
	Knows AI principles (e.g., ML)	3.36	0.97	Moderate
	Understands AI perception (seeing, hearing)	3.61	1.02	High
	Compares AI concepts (deep learning vs ML)	3.57	1.01	High
	Mean	3.61	0.87	High
Usage	Proficient in AI tools	3.43	0.89	High
	Uses AI to solve daily problems	3.45	1.00	High
	Uses AI for learning	3.74	0.92	High
	Mean	3.54	0.84	High
Evaluation	Selects appropriate AI solutions	3.55	0.91	High
	Evaluates AI limitations	3.54	0.97	High
	Identifies AI-generated bias	3.53	0.94	High
	Skeptical about AI content	3.69	1.00	High
	Mean	3.58	0.80	High
Ethics	Adheres to ethical AI use	3.59	0.98	High
	Vigilant about privacy/security	3.70	1.05	High
	Reflects on AI's societal impact	2.94	1.21	Moderate
	Alert to AI misuse	3.76	1.03	High
	Mean	3.50	0.78	High
Overall AI Literacy		3.56	0.75	High

Table 2. Mean levels of AI literacy among the respondents

3.1.2. Students' Level of Motivation in Using AI

Table 3 presents the mean levels of students' motivation to use AI tools. The data showed moderate to strong motivation, with the highest ratings observed in the Intrinsic/Interest Value (M = 3.46, SD = 0.82) and Utility Value (M = 3.46, SD = 0.83) subcomponents of task value. This high recognition of the practical benefits of AI in both academic and everyday settings and the strong willingness to engage with it can be the result of their extensive use of AI in everyday applications (Ombale & Jajoo, 2024) and its role in improving academic efficiency (Zhou et al., 2024). Moreover, their enthusiasm is presumably motivated by digital literacy, curiosity, and the perceived importance of AI in future employment (Vázquez-Parra, Henao-Rodríguez, Lis-Gutiérrez & Palomino-Gámez, 2024).

In contrast, their moderate Expectancy Beliefs (M = 3.33, SD = 0.79) show their lack of full confidence in their ability to use AI technologies for academic purposes effectively, despite their strong AI awareness, usage, evaluation, and ethical understanding (Table 2). This suggests that high AI literacy cannot be equated with higher self-efficacy. According to the findings of Osman, Mohamad and Kasbun (2024) and Ruiz-Rojas, Salvador-Ullauri and Acosta-Vargas (2024), this gap can be explained by insufficient systematic technical training and institutional support. Similarly, the students' moderate perceived Cost (M = 2.72, SD = 0.87) reflects existing concerns about factors like time, cognitive effort, and opportunity costs associated with AI use.

Items on Motivational Beliefs toward AI Use		**Mean**	**SD**	**Description**
Expectancy	Confidence in learning AI	3.68	0.85	High
	Self-assessed AI knowledge	3.29	0.93	Moderate
	Comparative self-confidence	3.16	0.96	Moderate
	High self-expectation for AI use	3.20	0.98	Moderate
	Mean	3.33	0.79	Moderate
Attainment Values	Importance of AI competence	3.63	0.85	High
	Priority on AI development	3.35	0.87	Moderate
	Need for AI awareness	3.37	0.97	Moderate
	Skill development focus	3.41	0.94	High
	Mean	3.44	0.77	High
Utility Values	AI as a career tool	3.23	1.01	Moderate
	Boost in productivity	3.49	0.97	High
	Task simplification	3.44	0.97	High
	Academic benefits of AI	3.69	0.90	High
	Mean	3.46	0.83	High
Intrinsic/Interest Values	Enjoyment in AI use	3.44	0.94	High
	Positive experiences with AI	3.52	0.91	High
	Interest in AI trends	3.42	0.96	High
	Fun in learning AI	3.46	0.88	High
	Mean	3.46	0.82	High
Cost	Time-value justification	2.64	0.93	Moderate
	Perceived ease of learning	2.55	0.90	Moderate
	Time investment trade-off	2.90	1.05	Moderate
	Willingness to invest effort	2.77	1.05	Moderate
	Mean	2.72	0.87	Moderate
Overall Motives in Using AI		3.28	0.46	Moderate

Table 3. Mean levels of respondents' level of motivational beliefs in using AI

3.2. Comparative Statistics

3.2.1. Comparison of the Constructs of AI Literacy when Grouped by Sex and Academic Program

The independent samples t-test results for students' AI literacy, grouped by sex, are illustrated in Table 4. Statistically significant differences were reported in Evaluation ($t(148) = 2.525$, *p*-value = 0.013, $d = 0.437$), Ethics ($t(148) = 3.277$, p-value = 0.001, $d = 0.568$), and Overall AI Literacy ($t(148) = 2.198$, p-value = 0.029, $d = 0.381$), with female students exhibiting slightly to moderately higher AI literacy levels in these domains (Cohen, 1988; Brydges, 2019). This finding aligns with the results of Jang, Choi and Kim (2022) and Wang et al. (2025), who observed that female students often display greater ethical awareness, presumably because of their stronger moral reasoning and higher sensitivity to risks, fairness, and social impacts. Female students also exhibited slightly higher degrees of Awareness ($t(148) = 1.553$, p-value = 0.122, $d = 0.269$) and Usage ($t(148) = 0.805$, p-value = 0.422, $d = 0.140$) (Cohen, 1988; Brydges, 2019) of AI compared to male students; however, these differences were not statistically significant.

Constructs	Sex	Mean	SD	df	t	p-value	Cohen's d	Decision
Awareness	Male	3.46	0.91	148	1.553	0.122	0.269	Failed to Reject Ho
	Female	3.69	0.84					
Usage	Male	3.46	0.92	148	0.805	0.422	0.140	Failed to Reject Ho
	Female	3.58	0.79					
Evaluation	Male	3.35	0.88	148	2.525	0.013	0.437	Reject Ho
	Female	3.69	0.74					
Ethics	Male	3.21	0.79	148	3.277	0.001	0.568	Reject Ho
	Female	3.64	0.74					
Overall Literacy	Male	3.37	0.81	148	2.198	0.029	0.381	Reject Ho
	Female	3.65	0.70					

Table 4. Independent sample T-Test result on students' level of AI literacy based on sex

Table 5 presents the ANOVA results on students' AI literacy across academic programs. The analysis indicated no statistically significant differences among BEED, BSTM, and BSHM students across all dimensions (all p-values > 0.05). These results imply that the students have comparable levels of AI literacy, as supported by the obtained minimal effect sizes ($\omega^2 = 0.003$ to 0.033) (Cohen, 1988; Brydges, 2019). However, BSTM and BSHM students consistently displayed slightly greater levels of AI literacy across all domains than the BEED students. Although these differences were not significant, these trends may reflect the influence of other contextual factors, such as better digital literacy (Saklaki & Gardikiotis, 2024) and higher exposure to digital technologies in their curriculum (Lee, Oh & Hong, 2024).

Constructs	Program	Mean	SD	df	F	p-value	ω²	Decision
Awareness	BEED	3.43	1.00	(2,86.2)	1.084	0.343	0.003	Failed to Reject Ho
	BSTM	3.71	0.73					
	BSHM	3.65	0.86					
Usage	BEED	3.32	1.00	(2,79.0)	1.551	0.218	0.013	Failed to Reject Ho
	BSTM	3.63	0.83					
	BSHM	3.62	0.71					
Evaluation	BEED	3.41	0.96	(2,81.3)	1.023	0.364	0.004	Failed to Reject Ho
	BSTM	3.63	0.76					
	BSHM	3.65	0.72					
Ethics	BEED	3.23	0.90	(2,85.6)	2.862	0.063	0.033	Failed to Reject Ho
	BSTM	3.57	0.65					
	BSHM	3.62	0.75					
Overall AI Literacy	BEED	3.35	0.92	(2,81.8)	1.679	0.193	0.017	Failed to Reject Ho
	BSTM	3.64	0.66					
	BSHM	3.64	0.66					

Table 5. One-way ANOVA on students' level of AI literacy based on academic program

3.2.2. Comparison of the Constructs of Motivational Beliefs in Using AI when Grouped by Sex and Academic Program

Table 6 reveals the results of the independent samples t-test comparing students' motivational beliefs about employing AI by sex. No significant differences were identified across most domains (p-values > 0.05). This indicates a similar level of motivation among male and female students. Nonetheless, a significant difference emerged in Intrinsic/Interest Value, $t(148) = 2.041$, p-value = .043, $d = 0.354$, with females (M = 3.56, SD = 0.75) achieving slightly higher scores than males (M = 3.27, SD = 0.92) (Cohen, 1988; Brydges, 2019). This suggests that female students show a greater appreciation for the collaborative and creative uses of digital technologies than their male counterparts. They also tend to enjoy design-oriented tasks (Wajcman, 2000) and are more drawn to technologies that can generate creative outputs like multimedia presentations. In addition, they may approach AI with greater interest and reflective thinking, resulting in more significant intrinsic value (Yin & Goh, 2024).

Constructs	Sex	Mean	SD	df	t	p-value	Cohen's d	Decision
Expectancy	Male	3.29	0.91	81.0	0.442	0.659	0.079	Failed to Reject Ho
	Female	3.35	0.72					
Attainment Value	Male	3.33	0.91	77.6	1.184	0.240	0.214	Failed to Reject Ho
	Female	3.50	0.68					
Utility Value	Male	3.35	0.94	148	1.251	0.213	0.217	Failed to Reject Ho
	Female	3.52	0.77					
Intrinsic/ Interest Value	Male	3.27	0.91	148	2.041	0.043	0.354	Reject Ho
	Female	3.56	0.75					
Cost	Male	2.75	1.02	79.0	-0.351	0.726	-0.063	Failed to Reject Ho
	Female	2.70	0.78					
Overall Motivation	Male	3.20	0.52	148	1.625	0.106	0.281	Failed to Reject Ho
	Female	3.33	0.42					

Table 6. Independent sample T-test result on students' level of motivational beliefs in using AI

Table 7 shows the ANOVA results comparing students' motivational beliefs toward using AI across academic programs. No statistically significant differences were found among BEED, BSTM, and BSHM students across all constructs (p-values > .05). Effect sizes (η^2 = –0.000 to 0.005) were negligible, confirming that program affiliation had no to little influence on motivational beliefs (Cohen, 1988; Brydges, 2019)This suggests the greater role of digital culture and personal experiences in influencing motivation for AI use than disciplinary instruction alone (Yurt & Kasarci, 2024).

Constructs	Program	Mean	SD	df	F	p-value	η^2	Decision
Expectancy	BEED	3.16	0.921	(2,87.0)	1.184	0.311	0.005	Failed to Reject Ho
	BSTM	3.43	0.603					
	BSHM	3.38	0.789					
Attainment Value	BEED	3.31	0.875	(2,83.7)	0.688	0.505	-0.002	Failed to Reject Ho
	BSTM	3.47	0.725					
	BSHM	3.50	0.725					
Utility Value	BEED	3.31	0.987	(2,82.5)	0.781	0.461	-0.000	Failed to Reject Ho
	BSTM	3.51	0.774					
	BSHM	3.53	0.763					
Intrinsic/Interest Value	BEED	3.30	0.962	(2,83.8)	0.889	0.415	0.001	Failed to Reject Ho
	BSTM	3.53	0.727					
	BSHM	3.51	0.765					
Cost	BEED	2.85	0.957	(2,86.8)	0.960	0.387	0.001	Failed to Reject Ho
	BSTM	2.76	0.752					
	BSHM	2.61	0.870					
Overall Motivation	BEED	3.19	0.545	(2,84.0)	1.071	0.347	0.004	Failed to Reject Ho
	BSTM	3.34	0.407					
	BSHM	3.31	0.434					

Table 7. One-way ANOVA on students' level of motivational beliefs in using AI based on academic program

3.3. The Significant Relationship between the Level of AI Literacy and Motivational Beliefs toward AI Use

Table 8 presents the Pearson correlations between students' AI literacy dimensions and their motives in using AI. Results show that all AI literacy dimensions were significantly and positively correlated with Expectancy, Attainment, Utility and Intrinsic/Interest Values (p-values < 0.05), except for Ethics and Utility Value (p-value = 0.052). However, these correlations were only small to moderate (r = 0.20 to 0.35) (Cohen, 1988) And among the four AI literacy domains, only Usage consistently demonstrated the strongest positive relationships across these motivational constructs: Expectancy Beliefs (r = 0.29, p-value <.001); Attainment Value (r = 0.34, p- value <.001), Utility Value (r = 0.31, p-value <.001), and Intrinsic/Interest Value (r = 0.35, p-value <.001), indicating that students who are more proficient in using AI tools are more likely to find them useful, personally valuable, and enjoyable. From a theoretical standpoint, these links are best explained by the function of actual AI use in developing one's self-efficacy (Bandura, 1997), boosting value internalization (Wigfield & Eccles, 2000), and promoting autonomy and interest (Ryan & Deci, 2000). Also, according to previous studies, students begin to regard AI as critical to their future, supporting its importance to them (Luckin & Holmes, 2016; Van de Oudeweetering & Voogt, 2017).

Motivational Beliefs	Level of AI Literacy	Pearson's r	p-value	Decision
Expectancy	Awareness	0.24	0.011	Reject Ho
	Usage	0.29	<.001	Reject Ho
	Evaluation	0.27	0.001	Reject Ho
	Ethics	0.20	0.028	Reject Ho
Attainment Value	Awareness	0.25	0.013	Reject Ho
	Usage	0.34	<.001	Reject Ho
	Evaluation	0.31	0.005	Reject Ho
	Ethics	0.27	0.001	Reject Ho
Utility Value	Awareness	0.21	0.023	Reject Ho
	Usage	0.31	<.001	Reject Ho
	Evaluation	0.26	0.001	Reject Ho
	Ethics	0.18	0.052	Failed to RejectHo
Intrinsic/ Interest Value	Awareness	0.20	0.011	Reject Ho
	Usage	0.35	<.001	Reject Ho
	Evaluation	0.29	0.001	Reject Ho
	Ethics	0.23	0.028	Reject Ho
Cost	Awareness	-0.19	0.013	Reject Ho
	Usage	-0.29	<.001	Reject Ho
	Evaluation	-0.26	0.005	Reject Ho
	Ethics	-0.16	<.001	Reject Ho

Table 8. Pearson's correlation between AI literacy dimensions and students' motivational beliefs toward AI use (df = 148)

In contrast, all AI literacy dimensions were significantly and negatively correlated with perceived Cost (r = −0.16 to −0.29; p-values < .05), but all were described as weak correlations (Cohen, 1988). Notably, usage (r = -0.29, p-value <.001) showed the strongest negative correlation. This means that the more effective students are in using AI, the less effort and risks they experience. These findings underscore the need to enhance AI usage skills in reducing psychological barriers to AI adoption in learning environments.

3.4. The Significance of the Regression Model on Determining the Linear Relationship on Students' Level of AI Literacy and Motivational Beliefs toward AI Use

Table 9 shows the results of the multiple regression analysis examining the predictive influence of AI literacy dimensions on Expectancy Beliefs. The model was significant, $F(4, 145) = 3.61$, $R^2 = 0.091$; adjusted $R^2 = 0.065$, p-value = 0.008, indicating that the predictors collectively explained 9.1% of the variance in Expectancy Beliefs. However, none of the predictors: Awareness (B = -0.011, t = -0.082, p-value = 0.935), Usage (B = 0.208, t = 1.523, p-value = 0.130), Evaluation (B = 0.140, t = 0.795, p-value = 0.428), and Ethics (B = -0.051, t = -0.362, p-value = 0.718) were significant. This indicates that Expectancy Beliefs are influenced by students' overall AI literacy rather than any single domain. The relatively low explained variance further implies that Expectancy Beliefs may be shaped by numerous unmeasured variables like social interaction (Huang, Zheng, Wang, Yin, Wang, Ding et al., 2023), frequency and satisfaction with AI interactions (Parsakia, 2023), and perceived ease and attitude towards AI tools (Tiwari, Bhat, Khan, Subramaniam & Khan, 2023).

Independent Variable (AI Literacy)	Model Summary			ANOVA		Coefficients				
	R	R2	Adj. R2	F	Sig.	B	β	SE	t	p
Constant	0.301	0.091	0.065	3.61	0.008	2.315		0.306	7.560	< .001
Awareness						-0.011	-0.013	0.139	-0.082	0.935
Usage						0.208	0.221	0.137	1.523	0.130
Evaluation						0.140	0.143	0.176	0.795	0.428
Ethics						-0.051	-0.050	0.139	-0.362	0.718

Table 9. Regression analysis of AI literacy dimensions and expectancy beliefs of AI use

Table 10 shows the multiple regression results for AI literacy dimensions as predictors of Attainment Values in using AI. The results show that the utility of the predictive model was significant, $F(4, 145) = 5.23$, p-value < 0.001, $R^2 = 0.126$; adjusted $R^2 = 0.102$. This indicates that all of the predictors explained only a small amount of variance in Attainment Values (12.6%), characteristic of educational and psychological research, wherein motivational constructs are influenced by various interacting factors (Huang et al., 2023; Tiwari et al., 2023). Usage (B = 0.289, t = 2.211, p-value = 0.029) emerged as a significant positive predictor of Attainment Values. This means that for every one unit increase in Usage, Attainment Values are predicted to increase by 0.289 units, given that Awareness, Evaluation, and Ethics remain unchanged.

Independent Variable (AI Literacy)	Model Summary			ANOVA		Coefficients				
	R	R2	Adj. R2	F	Sig.	B	β	SE	t	p
Constant	0.355	0.126	0.102	5.23	<.001	2.226		0.294	7.585	< .001
Awareness						-0.141	-0.159	0.134	-1.054	0.294
Usage						0.289	0.314	0.131	2.211	0.029
Evaluation						0.104	0.109	0.169	0.615	0.539
Ethics						0.093	0.095	0.134	0.699	0.486

Table 10. Regression analysis of AI literacy dimensions and attainment values of AI use

The results further suggest that students who are better at using AI tools are more likely to find AI engagement personally meaningful. This may be attributed to the idea that efficient use of AI tools fosters familiarity and a sense of mastery, which, in turn, strengthens their belief in the value and relevance of AI to their academic goals and self-concept. This interpretation is consistent with the core principle of Expectancy-Value Theory (Wigfield & Eccles, 2000). In contrast, Awareness (B = -0.141, t = -1.054, p-value = 0.294), Evaluation (B = 0.104, t = 0.615, p-value = 0.539), and Ethics (B = 0.093, t = 0.699, p-value = 0.486) were not significant predictors of Attainment Values.

Table 11 presents the multiple regression analysis examining the influence of AI literacy dimensions on students' Utility Values in using AI. The analysis yielded a significant model $F(4, 145) = 4.25$, p-value = 0.003, accounting for a small proportion (10.5%) of the variance in Utility Values (R2 = 0.105, Adj. R2 = 0.080). Among the predictors, only Usage (B = 0.349, t = 2.429, p-value = 0.016) significantly and positively predicted Utility Values. Specifically, an increase by one unit in Usage corresponds to a 0.349 unit increase in Utility Values, assuming other domains remain constant. These findings show that the more students use AI tools effectively, the more useful they perceive them to be in accomplishing academic tasks and learning goals. This positive link likely stems from students personally experiencing the benefits of AI in academic tasks, which increases their impression of its utility. This supports the idea that hands-on use is more effective than passive awareness in shaping utility values, highlighting the need for AI-integrated instructional practices (Baca & Zhushi, 2024). The other predictors—Awareness (B = -0.134, t = -0.911, p-value = 0.364), Evaluation (B = 0.135, *t* = 0.727, p-value = 0.469), and Ethics (B = -0.053, *t* = -0.364, p-value = 0.716) did not significantly predict Utility Values.

Independent Variable (AI Literacy)	Model Summary			ANOVA		Coefficients				
	R	R2	Adj. R2	F	Sig.	B	β	SE	t	p
Constant	0.324	0.105	0.080	4.25	0.003	2.418		0.322	7.507	< .001
Awareness						-0.134	-0.139	0.147	-0.911	0.364
Usage						0.349	0.350	0.144	2.429	0.016
Evaluation						0.135	0.130	0.185	0.727	0.469
Ethics						-0.053	-0.050	0.147	-0.364	0.716

Table 11. Regression analysis of AI literacy dimensions and utility values of AI use

Table 12 presents the regression analysis for AI literacy dimensions predicting students' Intrinsic/Interest Values in using AI. The overall model was significant, F(4, 145) = 6.07, p-value <.001, R^2 = 0.143, Adj.R^2 = 0.120. This shows that only a small proportion (14.3%) of the variance in Intrinsic/Interest Values can be explained by all predictors. The results also show that among these predictors, Awareness (B = -0.267, *t* = -1.903, p-value = 0.059), Evaluation (B = 0.125, *t* = 0.708, p-value = 0.480), and Ethics (B = 0.051, *t* = 0.362, p-value = 0.718) had no significant effects except Usage (B = 0.431, *t* = 3.137, p-value =0.002) which has a positive relationship with Intrinsic/Interest. This indicates that, if the other predictors are kept constant, Intrinsic/Interest Value is expected to increase by 0.431 units for every one-unit increase in Usage.

Independent Variable (AI Literacy)	Model Summary			ANOVA		Coefficients				
	R	R2	Adj. R2	F	Sig.	B	β	SE	t	P
Constant	0.379	0.143	0.120	6.07	<.001	2.271		0.308	7.364	< .001
Awareness						-0.267	-0.284	0.140	-1.903	0.059
Usage						0.431	0.442	0.138	3.137	0.002
Evaluation						0.125	0.124	0.177	0.708	0.480
Ethics						0.051	0.049	0.140	0.362	0.718

Table 12. Regression analysis of AI literacy dimensions and intrinsic/interest values of AI use

The findings also implies that students who are more skilled in using AI tools are more intrinsically motivated to use them. As students use and explore AI, they likely develop novelty, autonomy, and competence, leading to higher intrinsic motivation (Nguyen, Agarwal, Malik & Pandey, 2025). Moreover, students' engagement becomes more pleasurable and self-rewarding as they gain confidence and proficiency with AI. This underscores the motivational value of self-directed, meaningful experiences (Cui, Jiang & Li, 2023).

Table 13 presents the multiple regression analysis predicting students' perceived Cost of using AI based on the four dimensions of AI literacy. The overall model was statistically significant, F(4, 145) = 4.18, p-value = 0.003, explaining 10.3% of the variance in perceived Cost (R2 =0.103; Adj. R2 = 0.079). This small but significant effect size indicates that students' perceptions of the effort, challenge, and emotional stress they associate with using AI are affected by their overall level of AI literacy. But among the predictors, only Usage was a significant negative predictor of Cost (B = -0.296, *t* = -1.984, p-value = 0.049). It implies that perceived Cost is expected to decrease by 0.296 units if Usage increases by one unit, assuming other predictors remain constant.

Independent Variable (AI Literacy)	Model Summary			ANOVA		Coefficients				
	R	R2	Adj. R2	F	Sig.	B	β	SE	t	P
Constant	0.321	0.103	0.079	4.18	0.003	3.728		0.335	11.132	< .001
Awareness						0.175	0.175	0.152	1.146	0.254
Usage						-0.296	-0.286	0.149	-1.984	0.049
Evaluation						-0.292	-0.271	0.192	-1.519	0.131
Ethics						0.129	0.175	0.152	0.848	0.398

Table 13. Regression analysis of AI literacy dimensions and perceived cost of AI use

Additionally, the results indicate that students with greater proficiency in using AI tools tend to experience lower psychological and effort-related barriers. This underscores the importance of practical and hands-on experiences with AI in increasing one's efficiency, familiarity, and confidence while also decreasing their anxiety or difficulty perceptions about AI. According to Bandura (1997), Wigfield and Eccles (2000), Sova et al.(2024) and Chan and Zhou (2023), students are more likely to perceive AI tools as beneficial and manageable as they gain direct experience and mastery, thereby reducing the cognitive and emotional burden attributed to new technologies.

4. Discussion

The descriptive statistics indicate that the students generally demonstrated a high level of AI literacy, reflected in their strong awareness, effective use of AI tools, sound evaluation of AI outputs, and a clear sense of ethical responsibility. This high literacy may be attributed to their regular exposure to AI-powered learning platforms and the growing incorporation of AI-related content in academic settings (Singh, Vasishta & Singla, 2024; Nikoulina & Caroni, 2024; Hermosura, 2025). Their ability to think critically about technology also appears to be reinforced by their positive views of AI's usefulness and ease of use (Davis, 1989; Vázquez-Parra et al., 2024). Nonetheless, concerns about credibility, data privacy, and institutional monitoring exist, affirming the observations of Hermosura (2025).

The students' high level of AI literacy appears to be accompanied by strong motivational orientations toward AI use. Descriptive data show that they generally demonstrated high motivation across the Task Value subdomains—Attainment, Utility, and Intrinsic/Interest Values. This implies that AI is strongly valued by the students, especially for its importance to their academic and personal lives. This validates the role of enjoyment and relevance as key drivers of motivation as described in the Expectancy-Value Theory of Wigfield and Eccles (2000). However, some students expressed limited confidence in their ability to use AI effectively, as reflected by their moderate Expectancy Beliefs scores. This finding is often linked to limited training, ethical uncertainties, or insufficient institutional support (Osman et al., 2024; Ruiz-Rojas et al., 2024; Zhou et al., 2024; Ambika & Priya, 2025). Likewise, their moderate Cost scores indicate ongoing concerns about the time, effort, and trade-offs associated with AI engagement.

Comparative analyses based on sex and academic program provided additional insights into students' AI literacy and motivational beliefs in using AI. Based on the t-test results, female students exhibited slightly to moderately higher evaluative skills and ethical reasoning toward AI than male students. This may reflect females' greater sensitivities to the benefits, risks, and moral implications of AI use (Jang et al., 2022). These findings underscore the relevance of gender-responsive approaches that can better recognize and cultivate diverse evaluative and ethical perspectives, leading to a more balanced and responsible AI use across learner groups (Wang et al., 2025). Although sex did not significantly influence students' Awareness and Usage of AI, the small effect sizes indicate that female students were more familiar and engaged with AI than their male counterparts. When compared by academic program, AI literacy levels were comparable. However, students from BSTM and BSHM programs consistently exhibited slightly higher literacy scores across all domains than BEED students. These differences imply that they have higher digital literacy (Saklaki & Gardikiotis, 2024) and digital tools are more frequently used in their curriculum

(Lee et al., 2024). While statistically nonsignificant, these patterns highlight the importance of considering disciplinary contexts when designing AI-related educational interventions.

In terms of motivational beliefs, male and female students demonstrated generally similar levels of motivation in using AI. However, a slightly higher intrinsic motivation was observed among females. This may be linked to their appreciation for collaborative and creative digital activities. As Wajcman (2000) noted, females are more attracted to design-focused activities, while Weber and Custer (2005) found that they are more motivated when using technology in creating visually attractive and/or personally meaningful outputs like multimedia presentations. These findings highlight the importance of designing AI learning experiences that sustain female students' interest. Finally, comparisons across academic programs revealed no significant differences, and their negligible effect sizes confirmed these. According to Yurt and Kasarci (2024) and Mohamed, Shaaban, Bakry, Guillén-Gámez and Strzelecki (2024), factors such as digital culture and personal experiences have a greater influence on motivation for AI use than disciplinary instruction alone.

These findings collectively indicate that while sex had a statistically significant but minimal influence on students' motivation, individual experiences and interactions with AI played a more decisive role. Consistent with this, the correlation analysis showed that nearly all domains of AI literacy showed small to moderate positive associations with students' motivational beliefs, except for Cost, which was negatively correlated with all domains. This pattern suggests that higher levels of AI literacy correspond to greater confidence, perceived usefulness, and enjoyment in using AI. Among the literacy domains, AI Usage exhibited the strongest positive correlations, highlighting the role of practical engagement in fostering motivation. This resonates with Bandura's Social Cognitive Theory (1997) and Ryan and Deci's Self-Determination Theory (2000), which both state the importance of mastery experiences, competence, and autonomy in building self-efficacy and motivation. Overall, these findings highlight the need for effective AI integration in education, given the impact of meaningful and efficient AI use in driving motivation.

Moreover, the significant associations between Evaluation and motivational beliefs suggest the need for promoting students' critical interactions with AI. This is to provide students with opportunities to do proper assessments of the benefits, limitations, and relevance of AI to their learning. Awareness and Ethics also showed weak correlations with motivations (except for the non-significant link between Ethics and Utility Value), suggesting that foundational knowledge of AI and moral awareness contribute to students' motivation. Notably, all AI literacy negatively correlated with perceived Cost, with Usage showing the strongest negative correlation. Although the association was weak, it shows that if students are good at using AI, the fewer barriers they will experience. This affirms the critical role of hands-on experience in reducing cognitive and emotional load (Yin & Goh, 2024). Collectively, these results further strengthen the need for integrating real-world and reflective AI tasks to boost students' motivation and adaptability to emerging technologies.

Multiple regression analyses provided clearer evidence of the influence of AI literacy on students' motivational beliefs. All predictive models were significant but exhibited relatively low effect sizes, indicating that while AI literacy collectively influences students' motivation, its impact is minimal. Behavioral research suggests that such small effects remain meaningful, as motivation is shaped by numerous contextual, personal, and situational factors. Among the four dimensions, Usage was the only consistent and statistically significant predictor of all Task Value subcomponents. Specifically, it positively predicted Attainment, Utility, and Intrinsic/Interest Values and negatively predicted Cost. In contrast, Awareness, Evaluation, and Ethics were not significant predictors of motivational beliefs. This suggests that students' motivation to use AI comes from their actual use or application of AI in their lives. This uniform, predictive role of AI use for all motivational beliefs highlights the role of practical experience in promoting students' engagement and reducing perceived barriers to AI use.

The framework proposed in this study offers an insightful and balanced approach to the multidimensionality of AI literacy as discussed in previous studies (Ma & Chen, 2024; Chun, Ning, Chen

& Wijaya, 2025; Hossain, Biswas, Khan & Khan, 2025). Similarly, prior studies on student motivation have examined the influence of expectancy and task value on technology adoption in academic settings (Yin & Goh, 2024; Wang, King, Chai & Zhou, 2023; Yurt, 2025). The novelty of this study is the integration of two research strands, namely AI literacy and motivational beliefs, through the lens of EVT. Its focus goes beyond mere assessment of skills and attitudes. But rather, this study offers a more comprehensive understanding of the relationship between students' psychological readiness and motivation to use AI technologies. In doing so, the study offers educators and institutions a stronger foundation for cultivating responsible, confident, and motivated AI users within the framework of Education 4.0.

5. Conclusions

This study illustrates the complex impact of AI literacy on students' motivational beliefs in using AI. Findings show that students possessed high levels of AI literacy, marked by strong awareness, effective use, evaluative skills, and ethical discernment—largely stemming from their growing exposure to AI tools that are increasingly integrated into education. These findings encourage HEIs to continuously integrate AI-related content in their curriculum to provide students with more opportunities to strengthen their AI literacy. With this, HEIs can help promote responsible and meaningful use of AI that is reflective of global ethical standards in education. Students' perceived values of AI in terms of Attainment, Utility, and Intrinsic motivation are also high. This suggests that they view it as meaningful, useful, and enjoyable. However, with moderate scores in Expectancy Beliefs and Cost, students are still uncertain of their ability to use AI effectively or feel overwhelmed by its more demanding learning requirements. Bridging these motivational gaps will require HEIs to provide students with training in AI, focused workshops, instructional modules for use at the school level, and mentoring programs to increase their confidence and lower the perceived costs of using it.

Comparative analyses yielded a gender-specific pattern at least for evaluations, ethical and intrinsic motivation, with female students showing slightly to moderately higher evaluations and ethical orientations, as well as slightly higher intrinsic motivations. These results highlight the need for effective gender-inclusive AI education that will acknowledge and support multiple motivations and perspectives. Thus, curriculum designers need to employ an inclusive pedagogy that will facilitate both analytical and generative AI learning. There are also strategies available to make AI more engaging and accessible for all students, such as promoting group work, case-based discussions of ethical issues, and using gender-sensitive examples. Despite the lack of associations between students' academic program to either their AI literacy or motivation, the subtle variations observed across groups revealed the role of curricular exposure and digital culture. This points out the need for discipline-specific AI-related training to make learning more meaningful and relevant. Significant but weak associations were identified between AI literacy and students' motivational beliefs. Although correlation analysis revealed significant links in nearly all domains of AI literacy, the regression analyses showed that Usage was the only significant predictor of Task Values. This highlights the vital role of hands-on AI experience in enhancing students' motivation toward AI technologies. It is therefore recommended for institutions to create more opportunities for students to actively use AI tools in authentic tasks, helping them better appreciate AI's relevance, increase their interest and enjoyment, and reduce the perceived effort or cost associated with its use.

From a pedagogical standpoint, the findings offer valuable insights for curriculum design. They emphasize the impact of combining technical competencies and motivational support in bridging the gap between technical competence and meaningful engagement. To achieve this, curriculum frameworks should include inquiry-based and reflective learning tasks that promote AI use while developing students' self-efficacy and value perceptions. By aligning AI instruction with experiential and value-based learning principles, educators can effectively boost confidence, ethical reflection, and long-term enthusiasm in interacting with AI tools among students. In conclusion, this study highlights that proficient use of AI can greatly increase students' motivation to engage with AI technologies. By integrating AI applications in a meaningful and responsible way, HEIs could empower students with values alongside the practical expertise needed for the digital era to stimulate confidence and motivation to apply AI responsibly. Future studies might extend this work by investigating how AI literacy and motivation evolve through longitudinal studies, assessing actual usage behaviors alongside self-perceptions, and examining the impact of AI-integrated training across various institutional and disciplinary settings. Such directions might help to clarify how AI readiness needs to be cultivated in different educational settings.

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References

Ambika, G., & Priya, V. (2025). Perception on Usage of Artificial Intelligence Tools among B.Ed. Students. *International Journal of Emerging Knowledge Studies.*, 4(2), 78-88. https://doi.org/10.70333/ijeks-04-02-s-015

Baca, G., & Zhushi, G. (2024). Assessing attitudes and impact of AI integration in higher education. *Higher Education Skills and Work-based Learning,* 15(2), 369-383. https://doi.org/10.1108/heswbl-02-2024-0065

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. Macmillan.

Barron, K.E., & Hulleman, C.S. (2015). Expectancy-Value-Cost model of motivation. In *Elsevier eBooks* (503-509). https://doi.org/10.1016/b978-0-08-097086-8.26099-6

Brydges, C.R. (2019). Effect size guidelines, sample size calculations, and statistical power in gerontology. *Innovation in Aging*, 3(4). https://doi.org/10.1093/geroni/igz036

Chan, C.K.Y., & Zhou, W. (2023). *Deconstructing Student Perceptions of Generative AI (GenAI) through an Expectancy Value Theory (EVT)-based Instrument.* arXiv (Cornell University). https://doi.org/10.48550/arxiv.2305.01186

Chiu, T.K., Ahmad, Z., Ismailov, M., & Sanusi, I.T. (2024). What are artificial intelligence literacy and competency? A comprehensive framework to support them. *Computers and Education Open*, 6, 100171. https://doi.org/10.1016/j.caeo.2024.100171

Chun, Z., Ning, Y., Chen, J., & Wijaya, T.T. (2025). Exploring the interplay among artificial intelligence literacy, creativity, self-efficacy, and academic achievement in college students: Findings from PLS-SEM and FsQCA. *Education and Information Technologies,* 30, 21283-21316. https://doi.org/10.1007/s10639-025-13617-2

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates. Available at: https://utstat.utoronto.ca/~brunner/oldclass/378f16/readings/CohenPower.pdf

Costa, J.F., Cangussu, C.L., Gonçalo, C.R., Reinoso, L.F., Lemos, A., Azevedo, S.S. et al. (2025). Education 4.0: The role of Artificial intelligence in the development of new skills. *Aracê.*, 7(2), 9448–9464. https://doi.org/10.56238/arev7n2-280

Cui, Y., Jiang, Z., & Li, Q. (2023). *AI Assistance and Service Usage.* Social Science Research Network. https://doi.org/10.2139/ssrn.4497014

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly,* 13(3), 319. https://doi.org/10.2307/249008

Eccles, J.S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology,* 53(1), 109-132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods Instruments &Amp Computers*, 28(1), 1-11. https://doi.org/10.3758/bf03203630

Farrokhnia, M., Banihashem, S.K., Noroozi, O., & Wals, A. (2023). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, 61(3), 460-474. https://doi.org/10.1080/14703297.2023.2195846

Ghomi, M., & Redecker, C. (2019). Digital Competence of Educators (DIGCOMPEDU): Development and evaluation of a self-assessment instrument for teachers' digital competence. In *Proceedings of the 11th International Conference on Computer Supported Education (CSEDU)* (541-548). Crete, Greece. https://doi.org/10.5220/0007679005410548

Hasanein, A.M., & Sobaih, A.E.E. (2023). Drivers and Consequences of CHATGPT use in Higher Education: Key Stakeholder Perspectives. *European Journal of Investigation in Health Psychology and Education*, 13(11), 2599-2614. https://doi.org/10.3390/ejihpe13110181

Hermosura, N.L. (2025). Analysis of college students' attitude towards using AI in their academic works. *World Journal of Advanced Research and Reviews*, 26(1), 3634-3639. https://doi.org/10.30574/wjarr.2025.26.1.1527

Hossain, Z., Biswas, M.S., Khan, N.A., & Khan, G. (2025). Artificial intelligence literacy among South Asian library and information science students: Socio-demographic influences and educational implications. *IFLA Journal*. https://doi.org/10.1177/03400352251331468

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

Huang, H., Zheng, O., Wang, D., Yin, J., Wang, Z., Ding, S. et al. (2023). ChatGPT for shaping the future of dentistry: the potential of multi-modal large language model. *International Journal of Oral Science*, 15, 29. https://doi.org/10.1038/s41368-023-00239-y

Jang, Y., Choi, S., & Kim, H. (2022). Development and validation of an instrument to measure undergraduate students' attitudes toward the ethics of artificial intelligence (AT-EAI) and analysis of its difference by gender and experience of AI education. *Education and Information Technologies*, 27(8), 11635-11667. https://doi.org/10.1007/s10639-022-11086-5

Lata, P., & Kumari, R. (2025). Embracing the 4th Industrial Revolution (4IR): Education 4.0 Trends and future Perspectives. *Shodh Sari-An International Multidisciplinary Journal*, 4(01), 328-339. https://doi.org/10.59231/sari7797

Laupichler, M.C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "Scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis. *Computers in Human Behavior Reports*, 12, 100338. https://doi.org/10.1016/j.chbr.2023.100338

Lee, Y., Oh, J., & Hong, C. (2024). Exploratory research on understanding university students' artificial intelligence literacy in a Korean university. *Online Journal of Communication and Media Technologies*, 14(3), e202440. https://doi.org/10.30935/ojcmt/14711

Li, X., & Hu, R. (2020). Developing and validating the digital skills scale for school children (DSS-SC). *Information Communication & Society*, 25(10), 1365-1382. https://doi.org/10.1080/1369118x.2020.1864002

Luckin, R., & Holmes, W. (2016). *Intelligence Unleashed: An argument for AI in Education.* London: Pearson Education. Available at: http://oro.open.ac.uk/50104/

Ma, S., & Chen, Z. (2024). The development and validation of the Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS). *IEEE Access*, 12, 146419-146429. https://doi.org/10.1109/access.2024.3468378

Mohamed, A.M., Shaaban, T.S., Bakry, S.H., Guillén-Gámez, F.D., & Strzelecki, A. (2024). Empowering theSalle Faculty of Education students: Applying AI's potential for motivating and enhancing learning. *Innovative Higher Education,* 50, 587-609. https://doi.org/10.1007/s10755-024-09747-z

Ng, D.T.K., Leung, J.K.L., Chu, K.W.S., & Qiao, M.S. (2021). AI Literacy: definition, teaching, evaluation and ethical issues. *Proceedings of the Association for Information Science and Technology*, 58(1), 504-509. https://doi.org/10.1002/pra2.487

Nguyen, M., Agarwal, R., Malik, A., & Pandey, R. (2025). Generative AI: elevating knowledge acquisition and retention and recall through autonomy, interactivity and engagement. *Journal of Enterprise Information Management*. https://doi.org/10.1108/jeim-08-2024-0433

Nikoulina, A., & Caroni, A. (2024). Familiarity, use, and perception of AI-Powered Tools in Higher Education. *International Journal of Management Knowledge and Learning*, 13. https://doi.org/10.53615/2232-5697.13.169-181

Ombale, N.Y.M., & Jajoo, N.D.N. (2024). Usefulness of AI in Day-to-Day life. *International Journal of Advanced Research in Science Communication and Technology*, 4(1), 487-492. https://doi.org/10.48175/ijarsct-19583

Osman, Z., Mohamad, R.K., & Kasbun, N. (2024). What Does it Take to Trigger Intention to Use Artificial Intelligence among Students in Higher Education Institutions? *International Journal of Academic Research in Business and Social Sciences*, 14(7), 1412-1429. https://doi.org/10.6007/ijarbss/v14-i7/22004

Parsakia, K. (2023). The effect of chatbots and AI on the Self-Efficacy, Self-Esteem, Problem-Solving and critical thinking of students. *Health Nexus*, 1(1), 71-76. https://doi.org/10.61838/hn.1.1.14

Portilla, J.E.N. (2025). Systematic Review: Artificial Intelligence (AI) in Education 4.0. *The Journal of Educators Online*, 22(3). https://doi.org/10.9743/jeo.2025.22.3.13

Rahman, M.K., Hossain, M.A., Ismail, N.A., Hossen, M.S., & Sultana, M. (2025). Determinants of students' adoption of AI chatbots in higher education: the moderating role of tech readiness. *Interactive Technology and Smart Education,* 22(3), 448-480. https://doi.org/10.1108/itse-12-2024-0312

Rane, N.L. (2024). Education 4.0 and 5.0: Integrating Artificial Intelligence (AI) for personalized and adaptive learning. *Journal of Artificial Intelligence and Robotics,* 1(1), 29-43. https://doi.org/10.61577/jaiar.2024.100006

Rosa, A.C.D., Dacuma, A.K.C., Ang, C.B., Nudalo, C.J.R., Cruz, L.J., & Vallespin, M.R.D. (2024). Assessing AI Adoption: Investigating Variances in AI Utilization across Student Year Levels in Far Eastern University-Manila, Philippines. *International Journal of Current Science Research and Review*, 07(05), 2699-2705. https://doi.org/10.47191/ijcsrr/v7-i5-31

Ruiz-Rojas, L.I., Salvador-Ullauri, L., & Acosta-Vargas, P. (2024). Collaborative working and critical Thinking: adoption of generative artificial intelligence tools in higher education. *Sustainability*, 16(13), 5367. https://doi.org/10.3390/su16135367

Ryan, R.M., & Deci, E.L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68-78. https://doi.org/10.1037/0003-066x.55.1.68

Saihi, A., Ben-Daya, M., & Hariga, M. (2024). The moderating role of technology proficiency and academic discipline in AI-chatbot adoption within higher education: Insights from a PLS-SEM analysis. *Education and Information Technologies,* 30, 5843-5881 . https://doi.org/10.1007/s10639-024-13023-0

Saklaki, A., & Gardikiotis, A. (2024). Exploring Greek Students' Attitudes Toward Artificial Intelligence: Relationships with AI Ethics, Media, and Digital Literacy. *Societies*, 14(12), 248. https://doi.org/10.3390/soc14120248

Siddiq, F., Gochyyev, P., & Wilson, M. (2017). Learning in Digital Networks – ICT literacy: A novel assessment of students' 21st century skills. *Computers & Education*, 109, 11-37. https://doi.org/10.1016/j.compedu.2017.01.014

Singh, E., Vasishta, P., & Singla, A. (2024). AI-enhanced education: exploring the impact of AI literacy on generation Z's academic performance in Northern India. *Quality Assurance in Education,* 33(2), 185-202 . https://doi.org/10.1108/qae-02-2024-0037

Sova, R., Tudor, C., Tartavulea, C.V., & Dieaconescu, R.I. (2024). Artificial Intelligence Tool Adoption in Higher Education: A Structural Equation Modeling Approach to Understanding Impact Factors among Economics Students. *Electronics*, 13(18), 3632. https://doi.org/10.3390/electronics13183632

Tiwari, C.K., Bhat, M.A., Khan, S.T., Subramaniam, R., & Khan, M.I. (2023). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education*, 21(3), 333-355. https://doi.org/10.1108/itse-04-2023-0061

Van De Oudeweetering, K., & Voogt, J. (2017). Teachers' conceptualization and enactment of twenty-first century competences: exploring dimensions for new curricula. *The Curriculum Journa*l, 29(1), 116-133. https://doi.org/10.1080/09585176.2017.1369136

Vázquez-Parra, J.C., Henao-Rodríguez, C., Lis-Gutiérrez, J.P., & Palomino-Gámez, S. (2024). Importance of university students' perception of adoption and training in artificial intelligence tools. *Societies*, 14(8), 141. https://doi.org/10.3390/soc14080141

Wajcman, J. (2000). Reflections on Gender and Technology Studies: In What State is the Art? *Social Studies of Science*, 30(3), 447-464. Available at: http://www.jstor.org/stable/285810

Wang, B., Rau, P.P., & Yuan, T. (2022). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour and Information Technology*, 42(9), 1324-1337. https://doi.org/10.1080/0144929x.2022.2072768

Wang, F., King, R.B., Chai, C.S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: the roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education*, 20, 51. https://doi.org/10.1186/s41239-023-00417-2

Wang, Z., Chai, C., Li, J., & Lee, V.W.Y. (2025). Assessment of AI ethical reflection: the development and validation of the AI ethical reflection scale (AIERS) for university students. *International Journal of Educational Technology in Higher Education*, 22, 19. https://doi.org/10.1186/s41239-025-00519-z

Weber, K., & Custer, R. (2005). Gender-based Preferences toward Technology Education Content, Activities, and Instructional Methods. *Journal of Technology Education*, 16(2). https://doi.org/10.21061/jte.v16i2.a.4

Wigfield, A., & Eccles, J.S. (2000). Expectancy–Value Theory of achievement motivation. *Contemporary Educational Psychology*, 25(1), 68-81. https://doi.org/10.1006/ceps.1999.1015

Wulyani, A.N., Widiati, U., Muniroh, S., Rachmadhany, C.D., Nurlaila, N., Hanifiyah, L. et al. (2024). Patterns of Utilizing AI-Assisted Tools Among EFL Students: The Need for Surveys in Assessment

Model Development. *LLT Journal a Journal on Language and Language Teaching*, 27(1), 157-173. https://doi.org/10.24071/llt.v27i1.7966

Yin, S.X., & Goh, D.H. (2024). Factors influencing university students' AI use and knowledge acquisition. *Proceedings of the Association for Information Science and Technology*, 61(1), 1162-1164. https://doi.org/10.1002/pra2.1218

Yurt, E. (2025). The interplay between Five-Factor personality traits and AI use motives in Turkish pre-service teachers: A canonical correlation analysis. *Current Psychology,* 44, 13756-13773. https://doi.org/10.1007/s12144-025-08175-2

Yurt, E., & Kasarci, I. (2024). A Questionnaire of Artificial Intelligence Use Motives: A Contribution to Investigating the Connection between AI and Motivation. *International Journal of Technology in Education*, 7(2), 308-325. https://doi.org/10.46328/ijte.725

Zaidy, A.A. (2024). The impact of generative AI on student engagement and ethics in higher education. *Journal of Information Technology, Cybersecurity, and Artificial Intelligence.*, 1(1), 30-38. https://doi.org/10.70715/jitcai.2024.v1.i1.004

Zhao, J. (2025). The role of learners' AI literacy and resilience in boosting their engagement and motivation in AI-based settings: From an achievement goal theory perspective. *Learning and Motivation*, 91, 102152. https://doi.org/10.1016/j.lmot.2025.102152

Zhou, X., Zhang, J., & Chan, C. (2024). Unveiling students' experiences and perceptions of artificial intelligence usage in higher education. *Journal of University Teaching and Learning Practice*, 21(06). https://doi.org/10.53761/xzjprb23

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