The International Review of Multidisciplinary Research
Volume 1, Issue 6, May 2026, pp. 450-465
https://doi.org/10.5281/zenodo.20494194

Assessing the Attitudes Towards Artificial Intelligence (AI) and AI Motivational Value Beliefs on Students' Mathematics Performance

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Article Details:

Received: 25 March 2026
Revised: 30 March 2026
Accepted: 9 April 2026
Published: 31 May 2026
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Recommended Citation:

Mascariñas, R. S., Casas, R. R. L., Baterzal, L. K. C., Verzosa, V. E., Candole, I. V. (2026) Assessing the Attitudes Towards Artificial Intelligence (AI) And AI Motivational Value Beliefs on Students' Mathematics Performance. The International Review of Multidisciplinary Research. 1 (), 450-465. https://doi.org/10.5281/zenodo.20494194

Index Terms:

teaching mathematics, descriptive-correlational design, AI attitudes, AI motivation, mathematics performance, Bohol, Philippines

Abstract. Artificial Intelligence (AI) is increasingly reshaping educational landscapes, yet its influence on student motivation and actual academic performance in developing country contexts remains less explored. This descriptive-correlational study assessed the relationship between Grade ten (10) students' attitudes and motivational value beliefs toward AI and their mathematics performance in a public secondary school in Loon, Bohol, Philippines, during the first quarter of School Year 2025–2026. Using a validated questionnaire, along with students' first-quarter mathematics grades, data from 81 respondents were analyzed via descriptive statistics and inferential statistics using Spearman's rho correlation coefficient. Results showed that students held positive cognitive and affective attitudes toward AI but exhibited negative behavioral attitudes, alongside uniformly high motivational value beliefs across all dimensions (expectancy, attainment, utility, intrinsic, and cost) with a grand mean of 2.77. Mathematics performance averaged 81.74 (Satisfactory level). While general AI attitudes did not significantly correlate with mathematics performance (rho = -0.160, $p > 0.05$), a significant weak negative correlation emerged between AI motivational value beliefs and mathematics achievement (rho = -0.278, $p < 0.05$), suggesting a possible trade-off in student focus where higher AI motivation is associated with slightly lower math performance. The study concludes that despite high AI motivation, students do not translate this into behavioral engagement or improved math performance, revealing a notable attitude-behavior gap. It is strongly recommended that the proposed AI and Mathematics Enrichment Plan be implemented to bridge this gap through integrated, hands-on learning experiences that connect AI motivation with tangible behavioral engagement and mathematics achievement.

Introduction

Modern education is changing significantly because of technology breakthroughs that are redefining the way that knowledge is taught and learned. This change offers education systems around the world both unprecedented possibilities and difficult challenges, especially in the crucial area of mathematics where student proficiency continues to be a major concern for national development.

Globally, the integration of Artificial Intelligence (AI) is at the forefront of this transformation, emerging as a potential solution to the pervasive challenge of providing personalized, quality education. International studies demonstrate that AI-driven tools such as intelligent tutoring systems and adaptive learning platforms can significantly enhance mathematical understanding by offering customized instruction. For instance, Meng et al. (2024) found that adaptive learning systems improved mathematics achievement scores more effectively than traditional instruction. However, this global interest is tempered by significant concerns. Research highlights that an overreliance on AI can stifle students' creativity and critical problem-solving skills, as algorithms often lack the capacity for human-like innovation and outside-the-box thinking (Benvenuti et al., 2023; Marrone et al., 2022). Furthermore, issues such as the "black box" nature of AI, which provides answers without transparent reasoning, and inherent algorithmic biases that can perpetuate educational inequalities, present substantial risks to cultivating a deep and equitable conceptual understanding of mathematics (Opesemowo, 2024).

Through the MATATAG Curriculum, which prioritizes digital literacy and 21st-century skills, the Philippine Department of Education (DepEd) has recognized this potential on a national level. Nonetheless, there are many challenges along the way. According to Blando (2025), the Philippines faces several significant challenges, such as disparities in teacher readiness and technology infrastructure. Studies by Werang and Radja (2022) and Bernardo et al. (2022) show how unequal access to technology worsens already-existing motivational and achievement gaps, especially in mathematics, further disadvantages public school students, making the digital divide crucial.

Locally, public high schools in the different parts of Region VII reflect these national challenges. Preliminary observations indicate a continued reliance on conventional teaching methods and low student engagement in mathematics. The potential of AI remains largely untapped due to significant resource constraints, including inadequate access to reliable technology, slow internet, and a lack of structured frameworks for implementing AI in mathematics instruction. This situation creates a critical disconnect, where students in the region are unable to benefit from the adaptive and personalized learning experiences that AI tools can provide, potentially widening the existing achievement gap.

Thus, by examining the relationship between high school students' AI motivational beliefs and their mathematical achievement in Region VII high school, this study aims to close a significant gap. A suggested, research-based Mathematics Performance Enrichment Plan as the end outcome. By supporting educators in integrating AI effectively, helping administrators make strategic decisions, and influencing DepEd policies to close the technological and motivational divide, this plan aims to yield real benefits while maximizing AI's potential to enhance learning outcomes for all students.

Theoretical Background

This study is grounded in two psychological theories: Expectancy-Value Theory (Wigfield & Eccles, 2000) and Social Cognitive Theory (Bandura, 1991). These frameworks explain how motivational beliefs about AI influence mathematics performance. Legal support is provided by DepEd Order No. 40, s. 2012 and Republic Act No. 10533.

Expectancy-Value Theory (Wigfield & Eccles, 2000) posits that motivation is shaped by students' belief in their ability to succeed (expectancy) and the value they assign to a task. In this study, expectancy refers to confidence in using AI tools, while value includes AI's utility, importance, and interest. Research shows that students who see AI's benefits and believe they can master it are more engaged in STEM (Wigfield et al., 2017; Khine, 2024). This theory is particularly relevant in the Philippine context, where technology access varies (Bernardo et al., 2022; Eltahir & Babiker, 2024). While Social Cognitive Theory (Bandura, 1991) emphasizes reciprocal interactions between personal factors, behavior, and environment, with self-efficacy as a central motivator. Self-efficacy—belief in one's capability to use AI—develops through mastery experiences, vicarious learning, and social persuasion (Bandura, 1991; DiBenedetto & Schunk, 2022). In Philippine schools, supportive environments and teacher modeling shape students' AI confidence (Li, 2025; Yılmaz, 2021; Sheoran & Kaur, 2024). The theory helps frame interventions to boost AI self-efficacy (Bernardo et al., 2022). Moreover, legal bases: DepEd Order No. 40, s. 2012 ensures ethical and safe use of AI in classrooms, while RA 10533 (K-12 Law) mandates technology integration and 21st-century skills, providing a policy foundation for AI adoption in mathematics education.

Statement of the Problem

This research assessed the relationship between students' attitudes towards AI and its motivational value beliefs on the mathematics performance of the Grade 10 students in one of the public schools in Loon, Bohol for school year 2025–2026 as basis for mathematics performance enrichment plan.
Specifically, this study seeks to answer the following queries:

1. What is the level of students' attitudes toward Artificial Intelligence (AI) in terms of:
   1.1 cognitive,
   1.2 behavioral; and
   1.3 affective?
2. What is the level of AI motivational value beliefs of the respondents in terms of:
   2.1 expectancy value;
   2.2 attainment value;
   2.3 utility value;
   2.4 intrinsic/interest value; and
   2.5 cost value?

3. What is the level of academic performance of the respondents in Mathematics?
4. Is there a significant relationship between respondents' attitudes towards AI and their academic performance in Mathematics?
5. Is there a significant relationship between respondents' AI motivational value beliefs and their academic performance in Mathematics?
6. Based on the findings, what mathematics enrichment plan may be proposed?

Statement of the Null Hypothesis

Based on the objectives of the study, the following null hypothesis will be tested at 0.05 level of significance:

H_{01}: There is no significant relationship between the respondents' attitudes towards AI and their academic performance in Mathematics.

H_{02}: There is no significant relationship between the respondents' AI motivational value beliefs and their academic performance in Mathematics.

Methodology

Research Design

This study employs a descriptive-correlational research design to examine the relationship between students' attitudes towards AI (cognitive, affective, behavioral), AI motivational beliefs (expectancy, attainment, utility, intrinsic/interest, cost), and mathematics performance among junior high school students. A descriptive-correlational design is a non-experimental method that describes variables and measures the degree of association between them without manipulation (Fraenkel et al., 2019), making it appropriate for describing current levels of attitudes, motivation, and performance while determining significant relationships without establishing causation. Anchored in Expectancy-Value Theory (Wigfield & Eccles, 2000) and Social Cognitive Theory (Bandura, 1991)—consistent with previous AI-education research (Khine, 2024; Bernardo et al., 2022; Al-khresheh & Alkursheh, 2024)—the operational design uses validated surveys to measure AI attitudes and motivational beliefs alongside official mathematics grades, with Spearman Rho analyzing relationships as used in recent AI-education studies (Dahri et al., 2025; Meng et al., 2024). This approach provides data-driven insights into how AI-related perceptions influence math performance, addressing critical gaps in Philippine-specific research.

Flow of the Study

The study begins with the input stage, where essential data is gathered by administering a validated survey questionnaire to measure students' attitudes towards AI and AI motivational beliefs, along with collecting students' final mathematics grades from school records as the dependent variable. In the process stage, the collected data undergoes rigorous statistical treatment using descriptive statistics (mean, standard deviation) to summarize AI attitudes, motivational value beliefs, and math performance, while Spearman Rho analysis determines the strength and direction of associations between motivational factors and achievement. Ethical considerations, such as anonymizing data and securing informed consent, were maintained throughout in compliance with DepEd guidelines. The final output stage synthesizes findings into an actionable Mathematics Performance Enrichment Plan, detailing strategies to leverage AI tools for enhancing motivation and achievement (e.g., AI-driven tutoring, gamified math apps), with recommendations tailored to teachers and policymakers, mirroring the transformative approach of studies like Ward et al. (2024). The study concludes by identifying limitations (e.g., sample size, regional focus) and suggesting future research directions, such as longitudinal studies on AI's sustained impact.

Research Environment

This study was conducted in one of the public schools in Loon, Bohol, during the first quarter of school year 2025–2026, which caters to junior high school students from Grades 7 to 10 from both coastal and upland barangays. The school is equipped with basic classroom facilities, a computer laboratory, and internet access, and implements the K to 12 Curriculum under the Department of Education. Selected for accessibility to researchers and readiness to integrate technological innovations, the school is transitioning to DepEd's Enhanced Curriculum, providing a timely context to examine AI-driven motivational beliefs and mathematics achievement. Despite resource constraints common in public schools—such as limited access to advanced AI tools compared to private institutions—initiatives like the DepEd Computerization Program have begun equipping schools with basic digital resources (Blando, 2025). This setting allows the study to explore pragmatic AI adoption strategies in resource-constrained environments, with all ethical guidelines under DepEd Order No. 40, s. 2012 strictly observed.

Respondents

This study involved Grade 10 junior high school students from the mentioned high school in Region VII, selected through stratified random sampling to ensure representation. The target respondents were enrolled during the 2025–2026 school year, with no prior formal training in AI to assess authentic motivational responses. Exclusion criteria include students with special learning needs or those participating in parallel AI education programs, as these factors may confound results. The selection prioritizes diversity in socioeconomic backgrounds and math proficiency levels to capture comprehensive perspectives on AI's motivational impact, mirroring the sampling frameworks used in comparable Philippine studies on technology integration (Muñoz, 2025; Blando, 2025). Parental consent and student assent were secured following DepEd Order No. 40, s. 2012 protocols, with data anonymization protecting participant identities throughout the research process. The distribution of the respondents of this study is presented in Table 1 below.

Distribution by Section	n	%
Grade 10- Liberty	26	32.10
Grade 10- Love	27	33.33
Grade 10- Loyalty	28	34.57
Total	**81**	**100.00**

Table 1. Distribution of Respondents

The distribution of participants across the three Grade 10 sections in one of the public schools in Loon, Bohol, as shown in Table 1, indicates a total sample of 81 students for the study. A closer examination of the distribution reveals a slight imbalance among the sections. Sections Love (33.33%) and Loyalty (34.57%) represent the largest portions of the population, followed closely by Section Liberty (32.10%). This sample size is sufficient to support quantitative analysis and provides an appropriate representation of the Grade 10 student population within the school for the purposes of this research.

Research Instrument

The study utilized standardized survey questionnaires (See Appendix) to comprehensively measure students' attitudes towards AI and their AI motivational beliefs in relation to mathematics performance. The Student Attitudes Towards AI (SATAI) questionnaire, adopted from Suh & Ahn (2022), measures attitudes across three components (cognitive, affective, behavioral) with 26 statements, demonstrating excellent internal consistency (Cronbach's $\alpha = 0.92$). The AI Motivational Beliefs Survey, adapted from Yurt & Kaşarcı's (2024) AI Use Motives Questionnaire, measures five dimensions (expectancy, attainment, utility, intrinsic/interest, and cost) with 20 statements, showing very high reliability (Cronbach's $\alpha = 0.89$). For both scales, respondents used a 4-point forced-choice Likert scale (4=Completely True to 1=Completely False) with no neutral midpoint. Official first-quarter mathematics grades were collected from school records, providing an objective academic outcome measure consistent with established methodologies in educational technology research (e.g., Ward et al., 2024).

Data Gathering Procedure

The study started with securing official approvals from the Department of Education (DepEd) division offices and the school administration, followed by orientation sessions for participating teachers and students to explain the study's purpose, confidentiality measures, and voluntary participation terms. Parental consent forms were distributed to comply with the Child Protection Policy. During the data gathering stage, researchers administered printed survey questionnaires in controlled classroom settings during regular class periods, with trained proctors monitoring sessions to prevent discussion and ensure standardized conditions. Follow-up sessions were scheduled for absent students within one week, and official mathematics grades were collected from school registrars using anonymized codes to maintain confidentiality. After data collection, researchers encoded survey responses into Minitab software, with 20% of entries cross-checked for accuracy through random sampling. Incomplete surveys (with >10% missing data) were excluded, while physical copies were stored securely in locked cabinets and digital files protected with encryption before conducting preliminary descriptive statistics.

Statistical Treatment of Data

The collected data underwent rigorous statistical analysis using descriptive and inferential techniques to examine the relationships between variables and answer the research questions. The specific statistical tools were selected based on the nature of the data and the objectives of the study, as outlined; (1) Frequency Count – this is used to count how many respondents belong to a specific category or how often a particular response occurs in the data and the results are reported both as absolute frequencies (the actual count) and relative frequencies (the percentage of the total sample), providing a clear numerical and proportional overview of response patterns; (2) Percentage – this tool was used to calculate a ratio that will be expressed as a fraction of 100; (3) Weighted Mean – this was used to determine the overall level of the respondents' attitude toward AI (across cognitive, affective, and behavioral dimensions) and their AI motivational value beliefs (including expectancy, attainment, utility, interest, and cost components), unlike a simple average, the weighted mean accounts for the prescribed scale values of each response option, ensuring an accurate representation of the degree or intensity of the measured constructs; and (4) Spearman's Rank-Order Correlation Coefficient (Spearman's rho) – this tool was utilized to test the significant relationship between attitude towards AI, motivational value belief and the respondents' academic performance in Mathematics.

Ethical Considerations

This study adhered to established ethical standards in research involving human participants, particularly junior high school students. Approval was obtained from the Department of Education (DepEd) and the school administration prior to data collection. Informed consent from parents or guardians and assent from student participants were secured, ensuring that participation was voluntary and that respondents could withdraw at any time without consequence. Confidentiality and anonymity were strictly maintained using coded data and secure storage of both digital and physical records, with all information used solely for research purposes. The study complied with DepEd Order No. 40, s. 2012 (Child Protection Policy), ensuring the protection of participants' rights, welfare, and dignity, and that no harm—psychological, emotional, or academic—was inflicted. Furthermore, the researchers upheld academic integrity by accurately reporting findings and properly acknowledging all sources, while promoting the responsible and ethical use of Artificial Intelligence (AI) within the context of education.

Results and Discussion

Level of Attitudes of the Respondents Towards AI

Cognitive

S/N	Indicators	WM	SD	Verbal Description
1	I think that it is important to learn about AI in school.	2.70	0.87	Positive
2	AI class is important.	2.36	0.81	Negative
3	I think that lessons about AI should be taught in school.	2.53	0.81	Positive
4	I think every student should learn about AI in school.	2.60	0.89	Positive
	Aggregate Mean	**2.55**		**Positive**
	Aggregate Standard Deviation		**0.85**	

Legend: 3.25-4.00- Very Positive;2.50-3.24- Positive ;1.75-2.49-Negative; 1.00-1.74-Very Negative

Table 2. Level of the attitudes of the respondents towards AI in terms of cognitive aspect

The level of the respondents' attitudes towards AI in terms of the cognitive aspect is presented in Table 2. This table shows that the respondents generally hold a p*ositive* overall attitude towards AI in the cognitive domain (Aggregate Mean = 2.55). This suggests a foundational recognition among students of AI's value in education, aligning with the *Expectancy-Value Theory* (Wigfield & Eccles, 2000), which posits that students are more likely to engage with a subject they perceive as useful. This aggregate positive perception is consistent with the literature; for instance, students who understand the broader applicability of digital skills are more likely to value them (Suh & Ahn, 2022). However, a critical nuance emerges upon examining individual indicators. The statement, "AI class is important," received a mean score of 2.36, which falls into the "Negative" range. This divergence is significant. While students agree on the general importance of learning about AI, they appear hesitant to endorse a dedicated course for it. This finding can be contextualized in the Philippine setting, where students often prioritize core subjects over emerging technologies due to perceived curricular pressures (Bernardo et al., 2022)..Furthermore, this reluctance might also be attributed to students' limited exposure to well-structured AI curricula, which hinders their ability to visualize its standalone importance—a common obstacle in adopting new technology subjects as noted by Blando (2025). In general, the results indicate a positive attitude among respondents toward learning about AI in the cognitive aspect. This may mean that while students recognize the importance of AI education, they remain cautious about dedicating a full class specifically to the subject.

Behavioral

S/N	Indicators	WM	SD	Verbal Description
1	I want to work in the field of AI.	2.27	0.79	Negative
2	I will choose a job in the field of AI.	2.25	0.72	Negative
3	I would participate in a club related to AI if there was one.	2.35	0.79	Negative
4	I like using objects related to AI.	2.44	0.77	Negative
5	It is fun to learn about AI.	2.65	0.65	Positive
6	I want to continue learning about AI.	2.54	0.82	Positive
7	I’m interested in AI-related TV programs or online videos.	2.56	0.85	Positive
8	I want to make something that makes human life more convenient through AI	2.57	0.81	Positive
9	I am interested in the development of AI.	2.48	0.74	Negative
10	It is interesting to use AI.	2.59	0.74	Positive
11	I think that there should be more class time devoted to AI in school.	2.44	0.85	Negative
12	I think I can handle AI well.	2.53	0.81	Positive
	Aggregate Mean	**2.47**		**Negative**
	Aggregate Standard Deviation		**0.78**	

Table 3. Level of the attitudes of the respondents towards AI in terms of behavioral aspect

The level of the respondents' attitudes towards AI in terms of the behavioral aspect is presented in Table 3. Overall, the respondents exhibit a negative behavioral inclination toward AI, as indicated by the aggregate mean of 2.47, interpreted as "Negative." This suggests that although students recognize some value in AI, they are not yet behaviorally inclined to participate in deeper, sustained, or career-oriented AI activities, aligning with Chan & Zhou (2023), who observed that perceived costs—including effort, risk, and ethical concerns—weaken intention to use AI. Several indicators show negative responses (items 1, 2, 3, 4, and 11), referring to commitments like choosing an AI job, joining AI clubs, or allocating more class time to AI. This hesitancy may reflect lack of confidence or preparedness, consistent with research showing that students hesitate to engage deeply with emerging technologies when lacking self-efficacy (Pan, 2020) and that structured guidance is needed before translating interest into action (Ng et al., 2021). Despite these negative tendencies, several items received positive behavioral descriptions, reflecting curiosity, enjoyment, and willingness to explore AI informally (items 5, 6, 7, 8, 10, and 12). This interest-driven attitude mirrors studies reporting high student enthusiasm for AI when exposed to interactive or media-based learning (Kong et al., 2021; Pellas, 2023). Positive responses to creativity and problem-solving items reflect recognition of AI's societal impact, aligning with research showing favorable impressions when AI is perceived as helpful and relevant (Chan & Hu, 2023; Setälä et al., 2025). The overall negative behavioral orientation may stem from limited hands-on training or structured exposure, as students often struggle to translate interest into behavioral engagement without adequate AI literacy training (Sanusi et al., 2022; Yau et al., 2022).

Affective

S/N	Indicators	WM	SD	Verbal Description
1	AI is very important for developing society.	2.65	0.73	Positive
2	I think AI makes people’s lives more convenient.	2.52	0.81	Positive
3	AI is related to my life.	2.15	0.85	Negative
4	I will use AI to solve problems in daily life.	2.27	0.79	Negative
5	AI helps me solve problems in real life.	2.43	0.79	Negative
6	I will need AI in my life in the future.	2.27	0.85	Negative
7	AI is necessary for everyone.	2.64	0.69	Positive
8	AI produces more good than bad.	2.48	0.73	Negative
9	AI is worth studying.	2.57	0.72	Positive
10	I think that most jobs in the future will require knowledge	3.07	0.88	Positive
	Aggregate Mean	**2.51**		**Positive**
	Aggregate Standard Deviation		**0.78**	

Table 4. Level of the attitudes of the respondents towards AI in terms of affective aspect

The level of the respondents' attitudes towards AI in terms of the affective aspect is presented in Table 4. The table reveals a critical divergence in the respondents' affective attitudes, with an aggregate mean of 2.51 falling just within the "Positive" range, yet individual indicators unveiling abstract approval tempered by personal reservation. The data shows strong positive agreement with AI's broad societal impact, such as "AI is very important for developing society" (WM=2.65) and "I think that most jobs in the future will require knowledge of AI" (WM=3.07, the highest score), demonstrating recognition of AI's macro-level importance and future career necessity. This interpretation is supported by De Leon et al. (2025), who reported a positive relationship between AI literacy and perceived usefulness of AI tools in education, and reflects broader trends where students increasingly view AI as essential for social development and employability (Ng et al., 2021). However, this consensus fractures when focus shifts from society to the personal. Indicators such as "AI is related to my life" (WM=2.15), "I will use AI to solve daily problems" (WM=2.27), and "AI helps me solve problems in real life" (WM=2.43) all received negative descriptions, indicating a significant "personal applicability gap" where students do not yet see AI as a tool for their immediate everyday challenges (Chiu et al., 2023). Furthermore, ambivalence is highlighted by the mixed response to AI's ethical value: "AI produces more good than bad" (WM=2.48) was viewed negatively, yet respondents agreed that "AI is necessary for everyone" (WM=2.64) and "AI is worth studying" (WM=2.57). This tension reflects a nuanced public discourse balancing excitement with caution, aligning with findings that public attitudes toward AI combine optimism about potential with concern for ethical and societal implications (Machado et al., 2023; Brauner et al., 2024).

Summary Level of Attitudes of the Respondents Towards AI

Components	**WM**	**SD**	**Verbal Description**
Cognitive Aspect	2.55	0.85	Positive
Affective Aspect	2.51	0.78	Positive
Behavioral Aspect	2.47	0.78	Negative
Grand Mean	**2.51**		
Grand Standard Deviation		**0.80**	**Positive**

Table 5. Summary on the level of the attitudes of the respondents towards AI

Table 5 shows that respondents manifest a positive overall attitude toward AI, with a grand mean of 2.51 (Positive). The results suggest that learners generally hold favorable perceptions of AI across cognitive and affective aspects, even though the behavioral aspect remains negative. This supports Otermans et al. (2025), who found that students' cognitive and affective attitudes positively predicted AI awareness, but behavioral attitudes did not significantly predict actual usage. The cognitive aspect obtained the highest mean (2.55), indicating positive beliefs about AI's usefulness and potential, aligning with Long and Magerko (2021) and Druga et al. (2022), who noted that students develop positive cognitive impressions when they understand AI's functions and real-world applications.

The affective aspect also shows a positive attitude (2.51), reflecting interest, enjoyment, and positive emotional responses, consistent with Dewi et al. (2023), who found that interactive and multimedia components enhance affective engagement in learning contexts. However, the behavioral aspect has a negative verbal description despite positive cognitive and affective components, suggesting a significant "attitude-behavior gap" where positive perceptions do not readily translate into concrete actions. Strzelecki (2023) confirms that strong cognitive and affective attitudes often fail to produce behavioral intentions when learners feel unprepared or lack support, highlighting self-efficacy as a critical barrier. Crucially, behavioral engagement with AI increases only when learners gain foundational competencies and literacy (Sanusi et al., 2022; Long & Magerko, 2021). The results yield a positive overall attitude toward AI, meaning respondents are mentally and emotionally ready to engage but require further exposure, training, and opportunities to translate attitudes into actual behavior, as Zhang et al. (2024) found that AI literacy significantly affects performance expectancy and behavioral intention to adopt AI technologies.

Level of AI Motivational Value Beliefs of the Respondents

Expectancy Value

S/N	**Indicators**	**WM**	**SD**	**Verbal Description**
1	I can learn the skills that enable effective use of artificial intelligence applications.	2.99	0.72	High
2	My general knowledge about artificial intelligence is more than sufficient compared to many.	2.77	0.76	High
3	I am better than most of my peers in effectively using artificial intelligence applications.	2.68	0.72	High

4	My potential to effectively use artificial intelligence applications surpasses many people in my surroundings.	2.77	0.75	High
	Aggregate Mean	**2.80**		**High**
	Aggregate Standard Deviation		**0.74**	

Legend: 3.25-4.00-Very High;2.50-3.24- High;1.75-2.49-Low; 1.00-1.74-Very Low

Table 6. Level of AI motivational value beliefs of the respondents in terms of expectancy value

The level of AI motivational value beliefs of the respondents in terms of expectancy value is presented in Table 6. The table reveals that respondents possess a high level of motivational value beliefs regarding their expectancy to effectively use artificial intelligence, as indicated by an aggregate mean score of 2.80, which falls within the “High” category. Respondents express strong confidence in their ability to learn the necessary skills for AI applications, with the highest mean score of 2.99. They also perceive their general knowledge about AI as more than sufficient compared to many others (WM = 2.77) and believe they outperform most of their peers in effectively using AI tools (WM = 2.68). Furthermore, respondents feel their potential to use AI surpasses many people in their surroundings (WM = 2.77). Although the standard deviation of 0.74 shows some variability, the overall trend indicates a robust motivational belief in their capabilities related to AI. These findings align with recent research highlighting the importance of expectancy beliefs in technology adoption. For example, Setälä et al. (2025) found that students perceived self-efficacy and motivation significantly influence their intention to use AI tools in educational settings. Similarly, Alejandro et al. (2024) reported that pre-service teachers’ expectancy beliefs positively predicted their readiness to integrate AI into teaching practices. Such expectancy values, rooted in Bandura’s (1997) social cognitive theory, are essential drivers for sustained engagement and successful adoption of new technologies (DiBenedetto & Schunk, 2022). Therefore, the respondents’ high motivational value beliefs suggest promising potential for active learning and deeper involvement with AI applications.

Attainment Value

S/N	Indicators	WM	SD	Verbal Description
1	The ability to effectively use artificial intelligence is important to me.	2.78	0.82	High
2	Learning and implementing innovations in artificial intelligence applications are a priority for me.	2.57	0.84	High
3	It is important for me to stay updated on developments related to artificial intelligence.	2.78	0.79	High
4	I attach great importance to strengthening my skills in using artificial intelligence applications.	2.65	0.79	High
	Aggregate Mean	**2.69**		**High**
	Aggregate Standard Deviation		**0.81**	

Table 7. Level of AI motivational value beliefs of the respondents in terms of attainment value

The level of AI motivational value beliefs of the respondents in terms of attainment value is presented in Table 7. The table shows that the respondents manifest a high level of attainment value toward artificial intelligence, as indicated by the aggregate mean of 2.69, which is verbally described as High. The items reflect the respondents' recognition of the importance of effectively using AI, prioritizing learning innovations in AI, staying updated on AI developments, and strengthening skills in AI applications. The high scores across these indicators suggest that respondents place significant personal importance on developing competence in AI-related skills and knowledge, implying that AI is viewed not only as a useful tool but also as an essential area for personal growth and professional development. Similar recent studies confirm that attainment value and positive expectancy-value beliefs are strong motivators for learning AI, as students who perceive AI skills as important for their future success are more likely to invest effort in learning about AI (Wang et al., 2023). This finding may be attributed to the increasing prominence of AI in various fields, motivating respondents to prioritize AI skills to remain competitive and relevant. The results suggest a readiness among respondents to commit to AI learning and development because they view it as aligned with their personal goals and values. It also implies that efforts to integrate AI education could build on this high attainment value to further encourage engagement and mastery. In general, the high attainment value indicates that respondents see AI not merely as an academic subject but as an important and meaningful part of their personal and professional identity.

Utility Value

S/N	Indicators	WM	SD	Verbal Description
1	Artificial intelligence applications will assist me in becoming a proficient professional.	2.85	0.73	High
2	Artificial intelligence enhances my overall efficiency, making my life more effective.	2.90	0.72	High
3	In daily life, artificial intelligence helps me streamline my tasks.	2.77	0.71	High
4	Artificial Intelligence, benefits me in various subjects and courses.	2.65	0.76	High
	Aggregate Mean	**2.79**		**High**
	Aggregate Standard Deviation		**0.73**	

Table 8. Level of AI motivational value beliefs of the respondents in terms of utility value

Table 8 presented the level of AI motivational value beliefs of the respondents in terms of utility value. The table shows that the respondents manifest a high level of utility value toward artificial intelligence, as indicated by the aggregate mean of 2.79, which is verbally described as High. The items reflect the respondents' recognition that AI assists in becoming a proficient professional, enhances overall efficiency and effectiveness, helps streamline daily tasks, and benefits academic performance across subjects. The high scores on these indicators suggest that respondents clearly perceive AI as a practical and useful tool that delivers tangible benefits in both personal and professional contexts, implying that AI is valued not only for its functional convenience but also for its instrumental role in achieving goals, improving performance, and enhancing productivity. Similar recent studies note that utility value is a powerful motivational driver, especially when learners perceive a direct connection between AI skills and real-world outcomes such as career readiness and academic success; students who see AI as useful and relevant are more likely to intend to learn and apply AI in their future contexts (Wang et al., 2023). This finding may be attributed to the pervasive integration of AI in modern workflows and educational settings, which reinforces perceptions of its practical relevance. The results suggest that respondents are motivated to engage with AI because they perceive clear and immediate advantages to its use. This high utility value provides a strong foundation for educational initiatives, as learners are likely to be receptive to AI instruction that emphasizes applicability and practical benefits. In general, the high utility value indicates that respondents view AI not just as an interesting innovation but as a meaningful and advantageous resource that contributes positively to their professional development, daily efficiency, and academic achievement.

Intrinsic/Interest Value

S/N	Indicators	WM	SD	Verbal Description
1	I take pleasure in using artificial intelligence applications.	2.67	0.77	High
2	I enjoy experiences related to artificial intelligence.	2.81	0.74	High
3	Following developments in artificial intelligence is an interesting activity for me.	2.77	0.69	High
4	Developing my skills in using artificial intelligence is a delightful learning process for me.	2.79	0.74	High
	Aggregate Mean	**2.76**		**High**
	Aggregate Standard Deviation		**0.74**	

Table 9. Level of AI motivational value beliefs of the respondents in terms of intrinsic/interest value

The level of AI motivational value beliefs of the respondents in terms of intrinsic/interest value is presented in Table 9. The table shows that the respondents manifest a high level of intrinsic or interest value toward artificial intelligence, as indicated by the aggregate mean of 2.76, which is verbally described as High. The items reflect that respondents take pleasure in using AI applications, enjoy AI-related experiences, find it interesting to follow AI developments, and consider skill development in AI a delightful learning process. The high scores across these indicators suggest that engagement with AI is driven not only by external benefits or personal importance, but also by genuine enjoyment and curiosity. This implies that learners are intrinsically motivated to interact with AI, finding the process inherently satisfying and intellectually stimulating. Recent educational research supports that learning environments designed to foster autonomy and curiosity enhance students' intrinsic motivation, which in turn promotes enduring engagement and enjoyment of the learning process (Wang et al., 2023). This finding may be attributed to the interactive, innovative, and often user-friendly nature of contemporary AI tools, which can make learning feel more like exploration than obligation. The results suggest that respondents are likely to voluntarily seek out AI-related activities and persist in learning even in the absence of external rewards, due to the inherent satisfaction they derive from the experience. Educators can leverage this high intrinsic value by designing learning environments that are exploratory, creative, and aligned with students' natural curiosity about AI. In general, the high intrinsic/interest value indicates that AI is viewed by respondents not just as a practical tool or a professional necessity, but as a genuinely enjoyable and interesting domain worthy of personal time and intellectual investment.

Cost value

S/N	Indicators	WM	SD	Verbal Description
1	Investing time and effort to learn artificial intelligence applications is worthwhile for me.	2.86	0.74	High
2	Learning artificial intelligence applications is an easy task for me.	2.78	0.81	High
3	I am inclined to sacrifice time from other activities to learn artificial intelligence applications.	2.72	0.78	High
4	I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence.	2.86	0.80	High
	Aggregate Mean	**2.81**		**High**
	Aggregate Standard Deviation		**0.78**	

Table 10. Level of AI motivational value beliefs of the respondents in terms of cost value

The level of AI motivational value beliefs of the respondents in terms of cost value is presented in Table 10. The table shows that the respondents manifest a high level of *cost value* toward artificial intelligence, as indicated by the aggregate mean of 2.81, which is verbally described as *High*. This is interpreted through the lens of *Expectancy-Value Theory (EVT)*, where cost represents the perceived negative aspects of engaging in a task. In this table, the items measure *positive perceptions of cost*, indicating that respondents do not perceive the investment of time, effort, or sacrifice required to learn AI as prohibitively high. The high scores across these indicators suggest that respondents *view the effort required to learn AI as worthwhile and acceptable*. They are willing to invest time, find the learning process relatively easy, and are inclined to prioritize AI learning over other activities. This implies that, for these respondents, the perceived *benefits (utility, attainment, and intrinsic value)* of engaging with AI outweigh the perceived *sacrifices and effort*. Recent studies indicate that when learners perceive the costs of learning a new technology as low or justified, they are more likely to persist and engage deeply with the subject (Perez et al., 2023). This finding is significant because it contrasts with common barriers to technology adoption, where perceived difficulty and high time investment often deter engagement. The results suggest that respondents do not see AI as an overly burdensome or inaccessible field. This favorable cost perception, combined with their high attainment, utility, and intrinsic value, creates a strong motivational profile for sustained AI learning. In general, the high-cost value indicates that respondents are *psychologically prepared to invest in AI learning*. They perceive the required effort as manageable and the trade-offs as acceptable, positioning them favorably to translate their positive attitudes into committed, long-term behavioral engagement with artificial intelligence

Summary of Respondents' Level of AI Motivational Value Beliefs

Components	WM	SD	Verbal Description
Expectancy Value	2.80	0.74	High
Attainment Value	2.69	0.81	High
Utility Value	2.79	0.73	High
Intrinsic/Interest Value	2.76	0.74	High
Cost Value	2.81	0.78	High
Grand Mean	**2.77**		**High**
Grand Standard Deviation		**0.76**	

Table 11. Summary on the level of AI motivational value beliefs of the respondents

Table 11 shows the respondents' motivational value beliefs toward Artificial Intelligence, with all components rated at a high level and an overall grand mean of 2.77. Respondents exhibit strong expectancy value, indicating they believe they can successfully engage with AI-related tasks. Similarly, attainment value is high, suggesting that they see AI skills as important to their personal goals and identity. Utility value is also rated highly, reflecting the perception that AI knowledge and skills are practically beneficial. Additionally, intrinsic or interest value is strong, showing that respondents find AI learning enjoyable and intrinsically motivating. Interestingly, cost value is also rated high, implying that respondents are aware of the effort and challenges associated with engaging in AI learning but remain motivated despite these perceived costs. This well-established motivational profile aligns with previous research by Chen et al. (2022), who found that high motivational beliefs across expectancy, attainment, utility, and interest values positively influence students' engagement with emerging technologies, even when they recognize the associated costs. Despite these high motivational beliefs, it is often the case that students face contextual and experiential barriers such as lack of hands-on opportunities or insufficient institutional support that limit the translation of motivation into active engagement and skill development. Therefore, these findings highlight the importance of designing instructional strategies and support systems that channel existing motivation into confident behavioral participation and competence in AI.

Level of Academic Performance of the Respondents in Mathematics

Level	Numerical Range	f	%
Outstanding	90-100	12	14.81
Very Satisfactory	85-89	7	8.64
Satisfactory	80-84	28	34.57
Fairly Satisfactory	75-79	34	41.98
Did not meet the expectations	below 75	0	0.00
Total		**81**	**100.00**
Mean		**81.74**	
St. Dev.		**5.47**	

Table 12. Level of academic performance of the respondents in Mathematics

The mathematics academic performance of the respondents, as shown in Table 12, reveals a distribution skewed toward the middle of the grading scale. Most respondents, 76.55%, fell within the "Fairly Satisfactory" (41.98%) and "Satisfactory" (34.57%) categories, indicating a general baseline of competency and comprehension among the students. While a notable portion performed at higher levels—with 14.81% achieving an "Outstanding" grade and 8.64% reaching "Very Satisfactory"—the overall academic profile is defined by this central clustering, as further evidenced by the mean score of 81.74. The absence of any grades "below expectations" and the moderate standard deviation of 5.47 suggest a consistent performance level across the group, with minimal extreme variance. This performance pattern may reflect the nature of modular or alternative learning environments, whereas noted by scholars such as Lederman (2021), assessment structures and pedagogical approaches can sometimes lead to a compression of grades. Consequently, while the data demonstrates successful course completion, it also highlights an opportunity to deepen mastery and challenge a greater number of students to reach the highest performance tier.

Relationship Between the Respondents' Attitudes Towards AI and their Academic Performance in Mathematics

Variables	Spearman's rho	Strength of Correlation	p - value	Decision	Remarks
Attitudes Towards AI and Mathematics Performance	-0.160	Negligible Negative	0.153	Do not reject Ho	Not Significant

***significant at p<0.05 (two-tailed)*

Table 13. Test of relationship between the respondents' attitudes towards AI and their academic performance in Mathematics

Table 13 reveals a negligible negative correlation between respondents' attitudes toward AI and their mathematics performance (Spearman's rho= -0.160). Since the p - value (0.153) is greater than the 0.05 level of significance, the null hypothesis (H_{01}) is not rejected. This indicates no significant relationship between the two variables. The relationship between attitudes toward AI and Mathematics performance was examined using Spearman's rank -order correlation. This non-parametric test was selected because the mathematics grades data (Shapiro-Wilk W = 0.8685, p-value< 0.001) did not meet the assumption of normality. This finding aligns with recent research, such as the study by Chiu et al. (2023), which found that student attitudes toward emerging digital technologies, including AI, are largely shaped by factors like perceived enjoyment and career relevance, which are often disconnected from core academic competencies like mathematical reasoning. Similarly, research by Sanusi et al. (2022) on AI literacy in schools concluded that while AI interest is high, its correlation with performance in traditional STEM subjects like Mathematics is weak, as math achievement is more strongly tied to foundational skill mastery and instructional quality rather than general technological attitudes. Therefore, while

cultivating positive AI dispositions is important, this result suggests it operates independently of mathematical proficiency, highlighting the need for targeted, subject-specific pedagogical strategies to improve student outcomes in each domain.
Relationship Between the Respondents' AI Motivational Value Beliefs and their Academic Performance in Mathematics

Variables	Spearman's rho	Strength of Correlation	p - value	Decision	Remarks
AI Motivational Value Beliefs and Mathematics Performance	-0.278*	Negligible Negative	0.012	Reject Ho	Significant

***significant at p<0.05 (two-tailed)*

Table 14. Test of relationship between the respondents' AI motivational value beliefs and their academic performance in Mathematics

Table 14 indicates a negligible negative correlation between respondents' AI motivational value beliefs and their Mathematics performance (Spearman's rho = -0.278). However, as the p-value (0.012) is less than the 0.05 level of significance, the null hypothesis (H_{02}) is rejected. This denotes a statistically significant relationship, thought weak and inverse. A Spearman's rank-order correlation was employed because the AI motivational value beliefs data did not meet the assumption of normality (Shapiro-Wilk W = 0.9032, p-value <0.001). This modest but significant inverse relationship suggests that students with higher motivation toward AI including perceptions of its utility, intrinsic interest, and personal importance tend to have slightly lower grades in Mathematics, or vice versa. This finding aligns with Chiu et al. (2023), which observed that strong interest in applied, interdisciplinary fields like AI can sometimes correlate with a comparative de-prioritization of effort in traditional core subjects when students perceive them as less directly relevant to their future goals. Similarly, Ng et al. (2021) noted that students highly motivated toward emerging technologies may exhibit varying academic profiles, where engagement in innovative domains does not necessarily translate to high performance in foundational subjects like Mathematics, particularly if instructional integration between the fields is lacking. While the relationship is weak, its statistical significance underscores a nuanced divergence in how students allocate cognitive and motivational resources across different academic domains.

Conclusion and Recommendation

Based on the findings of this study, it is concluded that while Grade 10 respondents exhibit strong, positive motivational value beliefs and favorable cognitive and affective attitudes toward Artificial Intelligence, these factors have no significant bearing on their academic performance in Mathematics, as evidenced by negligible and weak correlations. This indicates that math achievement is governed more by subject-specific pedagogy and foundational skills than by general technological attitudes. However, the notable gap between high AI motivation and negative behavioral intention—where students value AI but hesitate to pursue it actively—cannot be ignored, as it may limit their future engagement in AI-driven fields. Other influential variables, such as instructional quality, learning environment, and the transitional academic demands of Grade 10, likely play a more substantial role in shaping mathematics outcomes, highlighting the need for targeted interventions in both math education and experiential AI learning to bridge the divide between interest and application.

Considering the findings, it is recommended that the *Mathematics Performance Enrichment Plan* be formally adopted and implemented to directly bridge the gap between students' high AI motivation and their actual engagement and mathematics performance.

Mathematics Performance Enrichment Plan

Areas of Concern	Objectives	Strategies	Expected Outcome
A. Behavioral Engagement with AI	To increase student participation in AI-related activities	Conduct seminars and trainings to students related to AI career pathways Encourage students to participate in AI-related activities and competitions Provide recognition and incentives to students who show potential in AI fields Train students on how to participate in AI clubs and projects effectively	*Increased participation of students in AI-related activities*
B. Mathematics Performance Enhancement	To improve mathematics achievement through AI integration	Implement AI-based adaptive learning platforms Develop AI-assisted math tutoring program Create AI-generated personalized practice materials Train teachers in data-driven instructional adjustments	Improved mathematics performance

C. Teacher AI Integration Capacity	To equip teachers with AI integration skills	Conduct professional development on AI in mathematics education Provide hands-on training with AI teaching tools Establish peer mentoring system for AI integration Create repository of AI-enhanced lesson plans	Enhanced teacher AI integration skills
D. AI-Motivation and Math Performance Connection	To bridge the gap between AI motivation and math achievement	Design integrated AI-Mathematics learning modules Implement project-based learning connecting AI and math Develop assessment methods measuring both AI skills and math understanding Create recognition system for AI-Math integration achievements	Stronger connection between AI motivation and math performance Positive correlation between AI engagement and math grades
E. Access to AI Learning Resources	To ensure equitable access to AI tools and resources	Establish AI learning resource center Provide offline AI tools for limited connectivity Develop loan system for AI learning devices Create AI resource guides for independent learning	Equitable access to AI learning resources

Acknowledgements

To the Lord God Almighty who gives us knowledge, wisdom, and strength to pursue this study in times when we face challenges along this journey; to Dr. Maria Salud M. Delos Santos, Chairman of the Thesis Advisory Committee, for encouraging and supporting graduate school students to continue and finish their graduate studies; to Dr. Raymund C. Espina, Dean of the College of Education of Cebu Technological University, for being very supportive to students engaged in research work; to Dr. Emerson D. Peteros, the research adviser, who constantly inspires the researchers to continue despite difficulties and challenges, whose invaluable support gave the researchers enough strength to continue despite all odds; to the panelists, Dr. John V. De Vera, Dr. Reylan G. Capuno, Dr. Veronica O. Calasang, and Dr. Randy C. Mangubat, for their honest insights which are valuable in making this research more relevant and meaningful; to Mr. Felix A. Añasco Jr., School Head, for granting permission to conduct this study in one of the public schools in Loon, Bohol; to all respondents for giving their time in answering the questionnaires sincerely; and to all people who extended their support and whose names are unwritten here, thank you for your valuable time, effort, and assistance that made this work possible.

Funding

No external funding was received for this study.

Competing Interests Statement

The authors declare no competing interests.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study; all data used were obtained from previously published sources as cited in the reference list.

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Appendices

No appendices are attached to this study.