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Exploring AI Literacy Through the Expectancy-Value Framework: A Mixed-Methods Study of Chinese High School Students

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Abstract: Artificial intelligence is important because it has the potential to influence every aspect of our daily lives. From solving problems to creating new opportunities, artificial intelligence will be a huge part of the future society. This study aims to explore Chinese high school students' AI literacy from the four dimensions: awareness, usage, evaluation, and ethics by using the expectancy-value theory. A mixed-methods approach was employed, including surveys of 478 students to assess their understanding of artificial intelligence and how much they know about it, along with qualitative interviews to explore specific suggestions towards the improvement of AI courses in school and AI applications in their schoolwork. Quantitative findings revealed that there are significant differences in the four dimensions of AI literacy that are: ethics, awareness, usage, and evaluation with tenth grade students showing higher scores. Students' AI literacy was influenced by their expectancy and value beliefs. There is no significant difference between school types for awareness, evaluation, usage but ethics. These findings highlight the impact of AI-related resources on students' ethical perceptions. The structural equation modelling revealed the hypothesized model is a good representation of the data. Then the multi group equation modelling revealed the hypothesized model fits well across groups. Here, the groups mean students who participated in AI clubs or not. Qualitative themes highlighted the benefits of AI in enhancing productivity and learning, challenges in evaluating AI-generated information, ethical concerns about artificial intelligence usage, as well as the desire for more support and education to enhance AI literacy. The study emphasizes the importance of integrating AI literacy education into school curricula to enhance students' understanding and practical application of AI.

Keywords: AI literacy, expectancy, value.

1. Introduction

AI, also known as artificial intelligence, is the ability of a computer or robot to perform tasks associated with humans. Artificial intelligence has become a transformative force across various sectors, such as healthcare, finance, education, and entertainment. AI applications such as AI in medical diagnostics and AI-powered recommendation systems have a pervasive influence on people and society. The rapid advancement of AI technology is leading to its integration into everyday life as well as its potential to read and write, however, as time passed and AI technology became more popular, this concept expanded. Digital and technological literacy refers to the ability of being able to use digital tools effectively and understanding technology beyond devices.

AI literacy can be broken down into its four core components: awareness, which is understanding what AI is and its role in society; usage, meaning the ability to interact with and use AI tools and technologies; evaluation, which means the critical assessment of AI tools, understanding their strengths, limitations, and biases; lastly, ethics, meaning the awareness of the ethical implications of AI, including issues related to privacy, bias, and decision-making. UNESCO mentions that: "AI literacy is crucial for equipping individuals with the skills to critically engage with AI technologies and understand their implications." From this quote, the importance of understanding AI literacy is demonstrated.

China has a strong ambition towards becoming the world leader in AI by 2030 and the country has invested in artificial intelligence research, education, and industry to achieve their goal. Implementing AI education into high school curricula is important because students can be ensured that they understand how to effectively use AI in the future. This study investigates the AI literacy levels of students from varying places and school types in China through the lens of the expectancy-value theory. Therefore, this study aims to inform the changes that should be made in future AI curriculum development and policies about implementing AI in high school.

2. Theoretical Framework

2.1. Expectancy-Value Theory (EVT)

EVT suggests that students' performance and engagement in a task are determined by two factors: their expectation of success and the value they place on the task. The definition of expectancy are the beliefs about one's ability to succeed, whereas value is the perceived information or usefulness of the task. Scholars such as Eccles. et al developed and applied EVT in educational research. According to Eccles and colleagues [1], students are more likely to engage in tasks when they believe they can succeed and when they value the outcomes associated with those tasks.

2.2. Application to AI Literacy

In this study, expectancy refers to high school students' beliefs about their ability to succeed in learning AI concepts such as machine learning or using AI tools. Values can be broken down into different components: intrinsic, utility, attainment, and cost. Value in this context reflects how much students enjoy learning about AI (intrinsic), how useful they perceive AI skills to be for their future careers (utility), and whether they see AI literacy as aligning with their personal academic goals (attainment). The cost is defined as the sacrifices or efforts required to learn AI. This study posits that students who have higher expectancy and value regarding AI literacy are more likely to engage in AI learning activities and demonstrate higher proficiency in AI-related tasks.

2.3. Expectancy-Value Theory (EVT) in Assessing Student Perceptions of AI

The expectancy-value theory (EVT) provides a framework to understand student perceptions of generative AI, as explored by Chan and Zhou [2], who developed an EVT-based instrument to assess students' perceptions of generative AI in education. Their findings indicate a strong positive correlation between perceived value and students' intention to adopt AI, suggesting that educators could enhance AI adoption by emphasizing its benefits. Interestingly, perceived cost showed a weak negative correlation with intention to use, which may reflect a higher tolerance for challenges when value is evident. This insight underscores the importance of creating curricula that highlight AI's educational advantages, potentially boosting student engagement with generative AI technologies.

Wang et al. [3] expanded on this by examining the roles of supportive environments and expectancy-value beliefs in university students' intentions to learn AI. With a sample of 494 students, their research demonstrated that both the learning environment and students' expectancy-value beliefs significantly influence motivation toward AI literacy, moderated by demographic factors such as gender, study field, and year level. These findings suggest that supportive learning environments, tailored to specific student groups, may foster positive perceptions and engagement with AI, supporting educators in designing more inclusive and effective AI literacy programs.

2.4. Moderating Factors and AI Literacy Engagement

Moderating factors such as readiness, social good, and optimism play a role in students' intentions to engage with AI, as seen in Sing et al. [4]. Using the Theory of Planned Behavior, they found that readiness and optimistic attitudes towards AI can significantly enhance students' intentions to learn. Similarly, Sanusi et al. [5] found that there is no significant gender or school type differences, suggesting that AI-related skills may transcend demographic factors in diverse cultural settings.

By applying EVT, this study investigates how Chinese high school students' expectancy and value influence their AI literacy outcome. The findings aim to inform the design of AI literacy curriculum.

3. Literature Review

3.1. AI Literacy: Definition and Importance

AI literacy is defined as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" [6]. High school students are at a critical developmental stage where they are forming their identities, career aspirations, and worldviews. Introducing AI literacy at this stage can significantly influence high school students' future choices and attitudes, thus, the awareness towards AI literacy in high school students should be raised to a higher level. Prior research does not show how the four dimensions of awareness, value, ethics, and usage influence each other. This study reveals how these four dimensions contribute to high school students' AI literacy level.

3.2. High School Students' Perceptions and AI Literacy

Artificial intelligence (AI) is an increasingly integral part of modern education, offering both opportunities and challenges in fostering AI literacy among students. The studies by Parmar [7], Soesanto et al. [8], Zhang et al. [9], and Lee and Maeng [10] collectively explore how high school and middle school students perceive and engage with AI across various domains, including medicine, mathematics, ethics, and language learning. Despite differences in focus and methodology, these studies highlight shared themes around students' awareness, trust, and utilization of AI, while also underscoring significant limitations.

3.2.1. Shared Emphases on AI Awareness and Applications

All four studies emphasize the importance of raising awareness and familiarity with AI among students. Parmar [7] revealed that 44.44% of high school students were unfamiliar with AI applications in medicine, and trust levels were notably low (23.53%), particularly among female students. Similarly, Soesanto et al. [8] found that Indonesian high school students generally recognized AI as a supportive tool, particularly in mathematics learning, where it could assist with problem-solving and visualizing complex concepts. Zhang et al. [9] extended the discussion to ethics and career futures, identifying how middle school students improved their understanding of AI's societal impacts and career implications through an integrated curriculum. Their findings suggest that age-appropriate AI learning, including simulations and games, can effectively enhance awareness. Lee and Maeng [10] also underscored students' awareness of AI applications, specifically chatbots in English learning, highlighting time-saving and user-friendly aspects, alongside ethical concerns related to plagiarism and copyright.

3.2.2. Addressing Gender Disparities and Ethical Considerations

A recurring theme is the need for equitable AI education. Parmar [7] identified gender disparities in familiarity and trust, suggesting empowerment initiatives to boost confidence among female students. Zhang et al. [9] highlighted the role of early AI education in promoting ethical reasoning and career awareness, emphasizing the value of integrating ethics into technical learning. Similarly, Lee and Maeng [10] found that students with prior AI learning experiences had a more positive view of chatbots, indicating the importance of inclusive and accessible AI education.

3.2.3. Methodological and Contextual Limitations

While these studies provide valuable insights, they share notable limitations. Parmar [7] and Lee and Maeng [10] both faced challenges with small, localized samples, limiting the generalizability of their findings. Soesanto et al. [8] acknowledged the lack of empirical testing and the narrow focus on a single demographic group in Indonesia. Zhang et al. [9], although innovative in their approach, were constrained by a small sample size due to the COVID-19 pandemic, further limiting the robustness of their conclusions. The shared limitations across these studies highlight the need for broader and more diverse sample populations to enhance the generalizability of findings. Furthermore, integrating qualitative data, such as student interviews and classroom observations, could provide deeper insights into students' experiences and perceptions of AI.

3.3. Integrating AI Literacy into Education

Recent studies by Casal-Otero et al. [6], Ng et al. [11], and Kong et al. [12,13] highlight shared priorities and challenges in integrating AI literacy into education, focusing on curriculum integration, teacher training, and ethical reasoning.

Casal-Otero et al. [6] conducted a systematic literature review of 179 documents from the Scopus database, identifying two primary approaches to AI literacy: learning experiences and theoretical perspectives. They advocate for integrating AI literacy into existing subjects rather than creating standalone courses, emphasizing the need for a competency framework to guide implementation. However, their review highlights the lack of rigorous assessments of students' understanding of AI concepts and notes the limitations inherent in relying solely on existing literature. Similarly, Ng et al. [11] emphasizes the importance of integrating both technical and ethical AI concepts into secondary school curricula, identifying the lack of standardized curricula and insufficient teacher training as key challenges. They recommend embedding AI literacy within broader curricula, supported by targeted teacher training programs. Despite the variability and scope limitations of their study, their findings underscore the importance of equipping educators to effectively deliver AI literacy content. Building on these insights, Kong et al. [12,13] provide empirical evidence from classroom interventions. Kong et al. [13] demonstrate how AI courses improved 128 senior secondary students' ability to apply AI concepts in real-world problem-solving and fostered metacognitive strategies for ethical reasoning through project-based learning (PBL). Meanwhile, Kong et al. [12] show how pre- and post-course tests with 141 students revealed improvements in AI literacy and ethical awareness. Both studies highlight the importance of sufficient learning time and the integration of ethics within technical AI education. However, these findings are limited by sample homogeneity and the use of newly designed instruments.

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Together, these studies emphasize the need for structured, integrated approaches to AI literacy. They advocate for embedding AI education into existing curricula, providing robust teacher training, and prioritizing ethical reasoning to prepare students for a future shaped by AI technologies. Despite limitations in scope, sample diversity, and empirical rigor, these findings offer actionable pathways for policymakers and educators aiming to advance AI literacy in K-12 and secondary education.

3.4. Gaps in Literature

While AI is becoming more global, few studies examine the impact of AI-focused curricula on students' critical evaluation skills in China. Therefore, understanding these dimensions is crucial for designing effective educational interventions. For example, my findings could inform the development of AI literacy programs in high schools across China. The study can introduce educators with information demonstrating the needs and challenges faced by students in learning about AI. Adjustments to the AI curricula provided by schools may also be altered after reading this paper. Most existing research often focuses on individual aspects of AI literacy but rarely explores different dimensions—such as awareness, usage, evaluation, and ethics. Research on AI literacy rarely considers how students' expectancy (belief in their ability to succeed) and value (perceived importance of AI education) influence their AI learning. When investigating these factors, insights into how to better engage students in AI-related courses is demonstrated.

The research questions guiding this study are:

1. What are the levels of AI literacy (awareness, usage, evaluation, and ethics) among Chinese high school students?
2. How do these four dimensions of AI literacy relate to each other?
3. Do AI literacy levels differ by grade level, school type, or AI course availability?
4. How do expectancy and value influence AI literacy?
5. Are these relationships consistent between students who participated in AI clubs and those who did not?

3.5. Hypothesis

The measurement model for AI literacy was tested using structural equation modeling (SEM), with AI literacy as a latent variable represented by four indicators: awareness, evaluation, usage, and ethics. The hypothesized relationships between the latent factor AI literacy and its indicators were modeled as follows:

$$\text{Awareness} = \lambda 1 \cdot \text{AI Literacy} + \epsilon A$$

$$\text{Evaluation} = \lambda 2 \cdot \text{AI Literacy} + \epsilon E$$

$$\text{Usage} = \lambda 3 \cdot \text{AI Literacy} + \epsilon U$$

$$\text{Ethics} = \lambda 4 \cdot \text{AI Literacy} + \epsilon Et$$

Where:

- A, E, U, and Et represent the observed indicators for **awareness**, **evaluation**, **usage**, and **ethics**, respectively.
- $\lambda 1$, $\lambda 2$, $\lambda 3$, and $\lambda 4$ are the factor loadings, indicating the strength of the relationship between the latent variable **AI Literacy** and each respective indicator.
- ϵA , ϵE, ϵU, and ϵEt represent the measurement error terms for each of the indicators, capturing the variance in the indicators not explained by the latent factor.

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Additionally, the AI literacy factor was posited to be influenced by two other latent factors, **expectancy** and **value**. The structural equation for AI literacy in relation to these factors was specified as:

$$\text{AI Literacy} = \alpha \cdot \text{Expectancy} + \beta \cdot \text{Value} + \zeta$$

Where:

- α and β are the paths linking **expectancy** and **value** to **AI literacy**, respectively.
- ζ represents the residual or unexplained variance in **AI literacy**.

These equations form the basis of the measurement and structural model tested in this study.

4. Method

4.1. Research Design

This cross-sectional mixed-method study examines AI literacy levels among Chinese high school students and differences by socioeconomic status. The design captures data at a single point, providing insights into students' current AI literacy.

4.2. Participants

The study sampled 478 high school students (grades 10–12) across China using simple random sampling. The sample included 172 private school students, 113 public school students, and 162 vocational school students, with 202 tenth graders, 151 eleventh graders, and 125 twelfth graders.

4.3. Instruments

The survey, adapted from the *Artificial Intelligence Literacy Scale*, consists of four sections: demographics, awareness, evaluation, ethics, and attitudes. Responses were collected on a 5-point Likert scale. A pilot test confirmed reliability (Cronbach's α: usage = .88, awareness = .53, evaluation = .54, ethics = .55), though awareness, evaluation, and ethics showed moderate reliability.

4.4. Data Collection

Survey data were collected online (Aug 12–Oct 31, 2024) with informed consent and ensured anonymity. Four female students participated in 20–25-minute interviews, discussing AI tool use, learning benefits, motivations, ethical concerns, and curriculum gaps. Topics also included peer, teacher, and parental attitudes toward AI and AI's role in future education and careers.

4.5. Data Analysis

Quantitative data were cleaned by removing incomplete responses and coding categorical variables. Analyses in SPSS 29 included descriptive statistics, t-tests, ANOVA, and regression. Multiple regression assessed predictors of academic performance, while structural equation modeling (SEM) tested relationships between expectancy-value theory and AI literacy. A multi-group SEM evaluated differences between AI club participants and non-participants. The model was tested with the model indices Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). Model fit was considered acceptable if RMSEA was below .08, SRMR was below .08, and CFI and TLI were above .[14].

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The qualitative data was analyzed using thematic analysis, following the framework of Braun and Clarke [15]. The software NVivo was used to first create some initial codes, and then generate the themes based on the initial codes. To ensure the trustworthiness of this study, several strategies were employed. Triangulation was used by examining multiple perspectives within the interview data to validate key findings on students' perceptions of AI. Thick description provided detailed, context-rich accounts of participants' responses, allowing for a deeper understanding of each perspective. Peer debriefing was conducted with a colleague experienced in qualitative research to review the themes and interpretations, reducing potential biases in data analysis. An audit trail was maintained throughout the research process, documenting decisions made during coding and theme development, ensuring transparency and replicability. Finally, reflexivity was practiced by the researcher to identify and account for personal biases, enhancing objectivity in the interpretation of findings. Together, these methods establish the study’s credibility, dependability, and confirmability.

5. Results

5.1. Descriptive Results

The descriptive statistics for the four aspects are as follows: **Awareness** had the highest mean score (M=3.42,SD=1.09), followed by **Evaluation** (M=3.34,SD=0.93), **Ethics** (M=3.32,SD=1.05M =), and **Usage** (M=3.31,SD=1.34). These results indicate relatively consistent scores across the aspects, with **Usage** displaying the highest variability.

Table 1: Correlation Between AI Literacy Constructs and Expectancy, Value

Categories	Awareness	Usage	Evaluation	Ethics	Expectancy	Value
Awareness	1					
Usage	0.244*	1				
Evaluation	0.46*	0.302*	1			
Ethics	0.32*	0.276*	0.411*	1		
Expectancy	0.322*	0.301*	0.458*	0.423*	1	
Value	0.44*	0.347*	0.52*	0.481*	0.418*	1

Note. *p < .001

Pearson correlations revealed moderate positive relationships between *awareness* and *evaluation* (r = .45), *awareness* and *ethics* (r = .44), and *awareness* and *value* (r = .46). The strongest correlation was between *evaluation* and *value* (r = .51), followed by *ethics* and *value* (r = .48), suggesting that better AI evaluation and ethical awareness are linked to higher perceived value. *Usage* showed weaker correlations with other constructs, indicating its lesser relationship with awareness, evaluation, and ethics. Expectancy and value are positively moderately correlated with the four dimensions of AI literacy.

5.2. ANOVA Analysis: Examining Group Differences by Grade Level and School Type

5.2.1. AI Literacy: Group Differences by Grade Level

Kruskal-Wallis tests examined AI literacy differences across grade levels (10th, 11th, 12th) due to normality violations (Shapiro-Wilk, p < .05). Significant differences were found in awareness, evaluation, ethics, and value. Post-hoc Mann-Whitney U tests with Bonferroni correction followed.

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- Awareness: Significant differences emerged, H(2) = 7.00, p = .03. Tenth-grade students (M = 3.51, SD = 1.04) reported higher awareness than twelfth graders (M = 3.20, SD = 1.00), p = .03. No other pairwise differences were significant.
- Evaluation: Significant differences were found, H(2) = 7.65, p = .02. Tenth graders (M = 3.49, SD = 1.00) outperformed eleventh graders (M = 3.19, SD = 0.95), p = .02. Other comparisons were non-significant.
- Ethics: A significant effect was observed, H(2) = 6.99, p = .03, but post-hoc tests did not confirm specific group differences.
- Value: A significant difference appeared, H(2) = 10.45, p = .01. Tenth graders (M = 3.50, SD = 0.95) rated AI value higher than eleventh graders (M = 3.17, SD = 0.82), p = .006. Other comparisons were non-significant.

5.2.2. AI Literacy: Group Differences by School Type

A Kruskal-Wallis test examined AI literacy differences across school types (public, private, vocational). No significant differences were found in **Awareness** (*H*(2) = 2.52, *p* = .283), **Usage** (*H*(2) = 1.73, *p* = .422), or **Evaluation** (*H*(2) = 1.07, *p* = .586). However, a significant difference emerged in **Ethics** (*H*(2) = 6.60, *p* = .037).

Post-hoc Mann-Whitney *U* tests with Bonferroni correction showed:

- **Public vs. Private**: Significant difference (*U* = 7950.00, *p* = .011).
- **Public vs. Vocational**: No significant difference (*U* = 15004.50, *p* = .112).
- **Private vs. Vocational**: No significant difference (*U* = 11785.00, *p* = .267).

These results suggest that public and private school students differ significantly in AI-related ethical perceptions, while vocational school students did not significantly differ from either group.

5.2.3. AI Literacy: Group Differences by AI Course Availability

A Kruskal-Wallis H test revealed a significant difference in **Ethics** scores based on the availability of AI-related resources, *H*(2)=7.03, *p*=.03, while differences in **Awareness**, **Usage**, and **Evaluation** scores were not significant. Post-hoc Mann-Whitney U tests indicated that schools with no AI-related resources scored significantly lower on **Ethics** compared to schools offering AI-related resources, *U*=15,337.00, *p*=.010. No significant differences were found between other pairs. These findings highlight the impact of AI-related resources on students' ethical perceptions.

5.3. Structural Equation Modeling Results

5.3.1. Model Fit

The hypothesized structural equation model was tested using Mplus Version 8.3. The model fits the data well, as indicated by the following fit indices:

$\chi 2(8)=11.55$, *p*=.173; Comparative Fit Index (CFI) = .994; Tucker-Lewis Index (TLI) = .990; Root Mean Square Error of Approximation (RMSEA) = .030 (90% CI [.000, .066]); and Standardized Root Mean Square Residual (SRMR) = .018. These indices suggest that the model is an excellent representation of the data.

5.3.2. Measurement Model

The latent variable AI Literacy was defined by four indicators: awareness, evaluation, usage, and ethics. All factor loadings were statistically significant (*p*<.001). The standardized loadings ranged

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from .448 (evaluation) to .702 (usage), with the strongest contribution coming from usage (see Table 1).

5.3.3. Structural Model

Both expectancy (β=.40,SE=.042,p<.001) and value (β=.60,SE=.039, p<.001
β=.60, SE=.039, p<.001) were significant positive predictors of AI literacy. Together, these predictors explained 71.0% of the variance in the latent variable (R^2=.71). The correlation between expectancy and value was moderate (r=.42, p<.001).

5.3.4. Modification Indices

A suggested modification index (MI=9.25) indicated adding a covariance between usage and awareness. However, this modification was not applied because the hypothesized model already achieved a good fit and theoretical justification for the covariance was not established.

Table 2: Standardized Factor Loadings for Latent Variable AI Literacy

Indicator	Standardized Loading	SE	p
Awareness	.57	.037	<.001
Evaluation	.45	.042	<.001
Usage	.70	.031	<.001
Ethics	.62	.034	<.001

Table 3: Structural Path Coefficients

Predictor	Outcome	Standardized β	SE
Expectancy	AI Literacy	.40	.042
Value	AI Literacy	.60	.039

5.4. Multi-Group Structural Equation Modeling Results

5.4.1. Model Fit

The multi-group structural equation model (SEM) examined differences in the relationships between expectancy, value, and AI literacy across two groups: students who participated in AI clubs (Club) and those who did not (No Club). The model achieved an excellent fit, as indicated by the following indices: $\chi2(23)$=28.49, p=.198, CFI = .991, TLI = .989, RMSEA = .032 (90% CI [.000, .065]), and SRMR = .046. These results suggest the hypothesized model fits well across groups.

5.4.2. Measurement Model

The latent variable **AI literacy** was defined by four indicators: **awareness**, **evaluation**, **usage**, and **ethics**. All factor loadings were statistically significant (p<.001) in both groups, with usage consistently showing the strongest standardized loading (Club: λ=.696, No Club: λ=.710; see Table 1).

5.4.3. Structural Model

The relationships between predictors (**expectancy** and **value**) and the latent outcome (**AI literacy**) were positive and significant in both groups. However, some differences were observed:

- In the **No Club** group, **expectancy** had a stronger effect (β=.442,p<.001) compared to the **Club** group (β=.349,p<.001).
- In contrast, **value** had a slightly stronger effect in the **Club** group (β=.616,p<.001) than in the **No Club** group (β=.572,p<.001).
- Correlation between **expectancy** and **value** was moderate in both groups (r=.438 in No Club; r=.395 in Club; p<.001).

Together, expectancy and value explained 74.5% of the variance in **AI literacy** for the No Club group and 67.2% of the variance for the Club group.

5.4.4. Group Differences

The magnitude of the paths from **expectancy** and **value** to **AI literacy** differed slightly between the groups, indicating potential moderation effects of AI club participation.

Table 4: Standardized Factor Loadings for AI Literacy

Indicator	No Club (λ)	Club (λ)	p (Both Groups)
Awareness	0.564	0.579	<.001
Evaluation	0.436	0.463	<.001
Usage	0.71	0.696	<.001
Ethics	0.637	0.601	<.001

Table 5: Standardized Structural Path Coefficients

Predictor	Outcome	No Club (β)	Club (β)	p(Both Groups)
Expectancy	AI Literacy	.442	.349	<.001
Value	AI Literacy	.572	.616	<.001

5.5. Qualitative Results

5.5.1. Perceived Benefits and Practical Uses of AI in Learning

Students appreciate AI's utility in managing academic tasks, improving productivity, and assisting with complex assignments. For example, participant 1 echoed that “GPT is mainly responsible for helping me with my academic work, such as when I need to look up references for writing papers.” They see AI as a valuable tool for both learning and organizing their studies, indicating a generally positive perception of AI’s practicality in their educational experiences. Participant 2 shared “Its biggest impact is helping me save time… so I don't have to ask teachers or other people I know one by one.” Also, Participant 3 said “I think it's most helpful for my studies because, for most things I don’t understand or areas where my logic is weak, AI can help me revise and improve them.”

5.5.2. Challenges and Caution in Using AI

Students often encounter challenges with AI’s reliability, which drives them to be cautious and critically evaluate AI-generated content. This theme captures the students' awareness of AI's limitations and the need for responsible use, suggesting a balanced view that includes both the benefits and limitations of AI. For instance, participant 1 mentioned that “One of the widely criticized points about GPT is its varying accuracy… it can provide fake links or generate incorrect information.” Similarly, participant 2 shared “AI doesn’t always provide correct information… if you ask it the same question or give it the same code, it may give different answers.” Additionally, participant 3

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said "I think a major prerequisite for using AI correctly is having good judgment… to sift through AI-provided information with personal discernment."

5.5.3. Creative Exploration and Ethical Concerns

Students use AI creatively, especially in fields like art and design, but this exploration brings up ethical concerns, such as originality and responsible use. This theme reflects their nuanced view of AI's potential in creative fields alongside the ethical boundaries they believe should guide its use. An example is that participant 2 said that: "I read an article before about AI as a romantic partner that continually meets demands… this might affect real moral values." Similarly, participant 3 said: "I think… during the design process, AI-generated renderings may have some mismatches… so it's necessary to narrow the scope and specify keywords." In addition, participant 4 also mentioned: "The school should provide more learning resources and opportunities regarding AI… AI is the trend of the future."

5.5.4. Need for Enhanced Support and Structured Learning in AI

Students express a desire for more structured support and resources to learn AI effectively, indicating a perception that current educational efforts may be insufficient. While they feel generally supported by parents, they desire formal instruction to build AI literacy and prepare for AI's growing role in future careers. For example, participant 1 said: "I hope my school can broaden the application of AI—not only offering computer courses but also providing some basic computer literacy classes." Additionally, participant 2 stated: "I think our school should promote this… reducing the fear of AI due to the unknown… it could also help us master some productivity tools for future learning and life." Similarly, participant 4 said: "The school should provide more learning resources and opportunities regarding AI… AI is the trend of the future."

Table 6: The Qualitative Results of Interviews

Themes	Initial Codes
Perceived Benefits and Practical Uses of AI in Learning	Variety of AI tools used, AI for Academic Support and Productivity, Efficiency and Time-Saving Benefits
Challenges and Caution in Using AI	Accuracy and Reliability Concerns, Critical Thinking and Judgement in Using AI
Creative Exploration and Ethical Concerns	Creative Use of AI in Arts and Design, Ethical Concerns and Potential for Misuse
Need for Enhanced Support and Structured Learning in AI	Desire for More AI Education and Literacy, Limited Parental Influence and Support, Influence of AI on Career and Job Roles

6. Discussion

The aim of this study was to evaluate the AI literacy levels of Chinese high school students in the four aspects: awareness, usage, evaluation, and ethics. This research provides insights for educators and policymakers on how to effectively integrate AI literacy education and address gaps in students' understanding.

Key findings indicate that Chinese high school students had the highest score in awareness because they are exposed to AI by social media or informal learning environments. In contrast, ethics and usage had a lower score because students did not receive formal and structured education on how to

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use AI, suggesting limited critical engagement with AI and practical application when students use AI. Expectancy and value beliefs were predictors of AI literacy. Additionally, participants of AI clubs demonstrated higher literacy levels because clubs provide more hands-on learning opportunities than traditional classrooms about AI, as well as allowing students to use their creativity to use AI in different ways. This finding raises concerns about accessibility, as students who do not participate in these clubs—due to resource constraints, lack of awareness, or competing academic priorities—may have fewer opportunities to develop AI-related competencies.

These findings align with the Expectancy-Value theory, which posits that students are more likely to participate in tasks which they think are meaningful. The results highlight that students' perceptions of AI's utility influence their likelihood of engaging with AI applications. Moreover, disparities in ethics education reveal the need for standardized frameworks and a more well-rounded curriculum in all kinds of schools.

Notably, higher evaluation and awareness scores for tenth grade students, indicating that earlier exposure to AI related topics can encourage greater participation. The lower scores in ethics for students in schools without AI resources show the importance of access to tools and training in shaping ethical awareness.

7. Implications

This study emphasizes insights of AI literacy among Chinese high school students. There are actionable implications for educators, policymakers, and technology developers that can be put into action. By following these implications, the gap between AI advancements and equitable access to Ai education can be connected.

7.1. Educational Implications

AI literacy education should not be categorized as a separate subject, instead, it should be embedded across disciplines, emphasizing interdisciplinary applications in math, science, and humanities. In schools, teachers should take mandatory training programs to equip educators with AI knowledge and teaching strategies. In addition, AI experts can also collaborate with schoolteachers to develop training modules.

7.2. Policy Implications

Due to the disparities of AI education for students in rural areas, online learning AI platforms, or government funding for under-resourced schools should be considered. The Chinese government should develop a standardized AI literacy framework to ensure consistency and quality in AI education across different parts of the country, along with scholarships for AI workshops, free access to AI tools, and internet subsidies for students who cannot usually have access to AI education.

7.3. Implications for Technology Developers

Technology companies should also communicate with schools to provide AI learning resources, mentorship opportunities, and internships for students. AI tools that are linguistically suitable for Chinese high school students should also be invented, aligning with educational goals and having easy accessibility.

7.4. Implications for Future Research

Future research can focus on the role of moderating factors like gender, socioeconomic status, and cultural expectations in affecting the AI literacy of teenagers. There should also be longitudinal

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studies to track students' change of AI literacy after the implementation of AI courses in school. Comparative studies across different regions and cultural contexts can also identify the best practices in AI literacy education. Lastly, some potential biases may be that the study includes self-report bias due to the reliance on participants' own assessments. In addition, the findings may be limited in generalizability due to the specific demographic characteristics of the participants.

8. Conclusion

Chinese high school students vary in AI literacy, with awareness highest and ethics most inconsistent. Expectancy and value predicted AI literacy, with distinct patterns among AI club participants. Integrating AI literacy into curricula is essential, and resource disparities must be addressed. Future research should explore longitudinal trends and socioeconomic influences. Fostering AI literacy is key to preparing students for an AI-driven future.

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