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Article

AI-Assisted Literary Reading: College Students' Acceptance and User Experience

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Abstract: Digital-era college students are reading less literature, thanks to information overload, short attention spans, and texts that can be hard to get through. Large language models (LLMs)—a type of AI—might offer a way to support literary reading. Using the Technology Acceptance Model (TAM), this mixed-methods study looked at 150 Chinese undergraduates and postgraduates, asking about their willingness to use AI for reading literature, how they actually use it, what drives that use, and what their experience is like. Tests show our measures are reliable (Cronbach's α = 0.970; KMO = 0.974, Bartlett's χ^2 = 2147.750, $p < 0.001$). Regression results suggest that two things seem to predict acceptance: AI that supplies background context (β = 0.255, p = 0.070) and enjoyable AI-led discussions (β = 0.268, p = 0.054). ANOVA and SNK post-hoc tests indicate that students who actively explore with AI have clearly higher acceptance (M = 4.2308) than those who are neutral (M = 3.1667). Students most often use AI to map character relationships, decode classical references, fill in historical background, and analyse writing techniques—though humanities and STEM majors differ in what they prioritize. Students appreciate how AI lowers barriers to reading, but they worry about becoming over-reliant and losing the ability to read deeply. The takeaway: AI should work as a cognitive scaffold, not a replacement for real literary engagement. This study offers practical pointers for weaving AI into literature teaching.

Keywords: AI-assisted reading; literary reading; Technology Acceptance Model (TAM); college students; humanities education; human-AI interaction

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1. Introduction

1.1. Research Background

Literary reading is a core component of humanities education, which undertakes the important functions of cultivating students' critical thinking, emotional empathy, cultural identity, aesthetic accomplishment, and value perception [1]. As a carrier of cultural heritage and spiritual connotation, literary works carry the emotions, thoughts, and social values of specific eras and groups. For college students, in-depth literary reading is not only a way to acquire knowledge but also an important path to shape personality, improve literacy, and establish a correct outlook on life and values. However, with the rapid development of digital media and the popularization of mobile internet, traditional literary reading is facing an unprecedented crisis. College students are in an environment of information overload and fragmented communication, and their reading time is continuously squeezed by short videos, social platforms, online games, and fragmented information. Their attention spans are shrinking gradually, and deep reading, immersive reading, and independent interpretation are gradually marginalized [2]. Educators generally worry that the "silent reading classroom" that focuses on in-depth text experience is disappearing, and the foundation of humanities education is being impacted.

Against this background, the rapid iteration of large language models (LLMs) such as ChatGPT, Kimi and ERNIE Bot has brought new opportunities for literary reading and teaching reform [3]. AI tools have powerful capabilities in text understanding, information extraction, content generation, logical reasoning, and interactive question answering [4,5]. They can help students sort out complex character relationships in long novels, explain obscure words and allusions in classical literature, analyze metaphor, symbol, contrast, and other writing techniques, supplement authors' life experiences, creative backgrounds and historical and cultural contexts, and even conduct in-depth interactive discussions around the theme, character image, and artistic value of literary works. These functions can effectively reduce the reading difficulty of classical Chinese literature, foreign classic novels, poetry, prose and other difficult works, improve reading efficiency and reading experience, and provide a new solution to the current dilemma of literary reading [6].

At present, a large number of studies have explored the application status, acceptance and influencing factors of AI in language learning, academic writing, academic literature reading and other fields, but there is still a significant research gap in the field of AI-assisted literary reading [7-9]. Different from academic reading that focuses on information acquisition, knowledge understanding and argument extraction, literary reading emphasizes aesthetic experience, emotional resonance, personalized interpretation and spiritual perception. The unique nature of literary reading determines that the application patterns and acceptance mechanism of AI in this field cannot be simply generalized from other educational scenarios. Therefore, it is urgent to carry out systematic empirical research on college students' acceptance status, real usage behavior, user experience and deep-seated influencing factors of AI-assisted literary reading.

1.2. Research Questions

This study takes the classic Technology Acceptance Model (TAM) as the theoretical framework, combines quantitative statistics and qualitative analysis, and focuses on the following four core research questions:

1. What is the overall acceptance level and distribution characteristics of college students for AI-assisted literary reading?
2. Based on the TAM framework, which key variables and specific perception items significantly affect college students' acceptance attitude and behavioral intention?
3. What are the specific usage scenarios, behavioral frequency, operation patterns and tool preferences of AI in college students' literary reading practice?
4. What are the perceived benefits, real concerns and in-depth experience feedback of college students when using AI for literary reading, and what are the differences between different groups?

1.3. Research Significance

The research conclusions of this study have important theoretical and practical significance. Theoretically, this study expands the application scope of TAM in the field of AI-assisted literary reading, enriches the empirical research system of human-computer interaction in humanities education, supplements the research results of AI application in literary education, and provides a theoretical reference and model basis for subsequent related research. Practically, this study truly restores the usage status and real needs of students, provides data support and practical guidance for educators and teaching managers to design scientific and reasonable AI-integrated literary teaching programs, helps balance the relationship between AI auxiliary tools and deep reading practice, and promotes the innovative development and high-quality progress of humanities education in the AI era.

2. Literature Review

2.1. Technology Acceptance Model (tam)

The Technology Acceptance Model (TAM) proposed by Al-Rahmi, et al [10]. is one of the most influential and widely used theoretical models for explaining and predicting users' technology adoption behavior. TAM holds that users' acceptance and use behavior of information technology are mainly determined by two core variables: first, perceived usefulness (PU), which refers to the degree to which users believe that using the technology can improve their task completion efficiency, work performance and learning outcomes; second, perceived ease of use (PEOU), which refers to the degree to which users believe that using the technology requires little effort, simple operation and low learning cost. These two variables jointly affect users' attitude toward use (ATU), that is, the overall emotional and evaluative tendency of using the technology, and then determine the behavioral intention (BI) and actual usage behavior (AUB) of users [10].

In recent years, with the rapid development of artificial intelligence technology, TAM has been widely used, verified and expanded in the field of AI education [11]. Liu and Ma applied TAM to explore college English learners' acceptance and Behavioral Intention of ChatGPT, and found that perceived usefulness is a key predictor of learners' behavioral intention [8,12]. Hu and Gong constructed an integrated model integrating TAM and Task-Technology Fit (TTF) to explain college students' Behavioral Intention of generative AI in second-language writing [7,13]. Xia, et al. expanded TAM by introducing variables such as perceived social presence, trust and reading anxiety, and confirmed that perceived ease of use significantly promotes students' behavioral intention to use AI-assisted reading tools [1]. Pan, et al. incorporated AI literacy and AI anxiety into TAM, and revealed the influencing mechanism of scholars' acceptance of AI-assisted academic literature reading. However, most of these studies focus on language learning, academic writing and academic reading, and there is a lack of targeted verification and expansion of TAM in literary reading scenarios with aesthetic and emotional characteristics [9].

2.2. AI-assisted Reading in Educational Contexts

AI-assisted reading tools have developed rapidly in recent years, covering multiple types such as general-purpose chatbots (ChatGPT), document reading assistants (ChatDOC, ChatPDF), professional literature management platforms (ivySCI, ReadPaper), and knowledge visualization tools (Connected Papers) [14]. These tools can provide diversified reading support services such as text translation, content summarization, intelligent question answering, concept sorting, literature comparison and mind map generation [15].

Existing research on AI-assisted reading mainly focuses on academic literature reading for graduate students and scientific researchers [16]. Pan, et al. found that AI literacy and AI anxiety significantly affect scholars' perceived ease of use, perceived usefulness and behavioral intention [9]. Oubibi, et al. confirmed that AI tools can improve scholars' digital academic writing ability and stimulate reading engagement and research enthusiasm [14,17]. However, literary reading is essentially different from academic reading. Literary reading focuses on aesthetic appreciation, emotional experience, personalized understanding and spiritual perception, rather than simple information extraction, knowledge memorization and argument comprehension [18]. This essential difference means that the application value, acceptance logic, usage risks and educational norms of AI in literary reading need to be re-examined and systematically studied [9,14].

2.3. AI Application in Humanities Education

The integration of AI into humanities education has triggered extensive academic debates and discussions. Supporters believe that AI can lower the threshold of literary reading, provide personalized learning support, improve learning efficiency, help students better understand difficult literary works, and stimulate reading interest and learning initiative [19,20]. Critics worry that over-reliance on AI will lead to homogenized interpretation, weaken students' independent thinking ability, critical thinking ability and creative interpretation ability, and erode the humanistic warmth, aesthetic experience and spiritual connotation that are the core of literary reading [21-23]. Joelving found through experimental tests that AI-generated literary commentary is structurally complete and fluent in language, but lacks unique textual perception, emotional depth and personalized thinking, showing obvious "modelization" and "homogenization" characteristics [18]. Fu, et al. proposed the "mirror theory" of AI application in education, arguing that AI is like a mirror that amplifies users' own abilities and literacy, so active and critical use is the key to leverage the value of AI. These debates fully highlight the necessity and urgency of empirical research on students' real experiences of AI-assisted literary reading [24].

3. Methodology

3.1. Theoretical Framework

This study takes the classic TAM as the core theoretical framework, and combines the characteristics of literary reading scenarios, the needs of college student groups and the research purpose to operationalize and define four core constructs:

Perceived Usefulness (PU): Students' belief that AI tools can improve their literary reading comprehension efficiency, deepen their understanding of text connotation, and help solve reading difficulties.

Perceived Ease of Use (PEOU): Students' perception of the simplicity, convenience, speed and low operation cost of using AI tools to complete literary reading tasks.

Attitude Toward Use (ATU): Students' overall emotional tendency, evaluation attitude and acceptance degree toward using AI for literary reading.

Actual Usage Behavior (AUB): Students' self-reported usage frequency, usage scenarios, operation patterns and future behavioral intention of AI in literary reading.

3.2. Questionnaire Design

This study developed a formal questionnaire with a total of 25 items based on the TAM framework, existing mature scales and literary reading scenarios. The questionnaire is divided into four parts:

Demographic information: 3 items, including grade level, academic major (humanities, science, engineering, etc.), and weekly literary reading time.

TAM core measurement scale: 15 items, using a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree) to measure the four core constructs of perceived usefulness, perceived ease of use, attitude toward use and actual usage behavior.

Usage scenarios and behavior patterns: 4 items, including main usage purposes, usage timing, perceived effects and commonly used AI tool types.

Open-ended questions: 3 items, collecting qualitative information such as students' specific reading experience, perceived advantages and disadvantages, and concerns about AI-assisted literary reading.

3.3. Participants and Data Collection

The research participants were 150 undergraduate and graduate students from multiple comprehensive universities and professional universities in China, covering humanities and social sciences, science, engineering, art and other disciplines. The questionnaire was distributed through online platforms such as university forums, course communication groups, social media and questionnaire stars. Participation was voluntary and anonymous, and all respondents were informed of the research purpose and data use scope in advance to ensure the objectivity, authenticity and validity of the data.

3.4. Data Analysis Methods

In this study, SPSS 26.0 statistical software was used to analyze the quantitative data, including reliability analysis (Cronbach's α coefficient), construct validity analysis (KMO test and Bartlett's test of sphericity), descriptive statistical analysis, Pearson correlation analysis, multiple regression analysis, univariate ANOVA and S-N-K post-hoc test. The qualitative data obtained from the open-ended questions were analyzed by thematic analysis method, and the core experience themes, benefit cognition and concern points were extracted and summarized.

4. Results

4.1. Reliability Analysis

Reliability analysis was used to test the internal consistency and stability of the 15-item TAM scale. The results showed that the standardized Cronbach's α coefficient of the total scale was 0.970, which is far higher than the threshold of 0.80 for excellent reliability, indicating that the scale has excellent internal consistency reliability. The item-total statistics are shown in Table 1.

Table 1. Item-Total Statistics of Reliability Analysis

Measurement Item	Corrected Item-Total Correlation	Cronbach's α If Item Deleted
AI helps clarify complex character relationships in foreign literature	0.811	0.968
AI explains words and allusions in classical literature	0.811	0.968
AI background information deepens text understanding	0.795	0.968
AI analyzes writing techniques and artistic features	0.819	0.968
Easy to ask AI literary questions	0.869	0.967
AI provides quick and convenient analysis	0.844	0.967
AI interface is clear and easy to use	0.830	0.967
AI query is more labor-saving than paper/web search	0.796	0.968
Like to use AI as a reading assistant	0.842	0.967
Discussing literature with AI is interesting	0.785	0.968
Willing to use AI more in the future	0.810	0.968
Positive attitude toward AI-assisted reading	0.796	0.968
Often use AI to query literary concepts	0.796	0.968
Actively use AI to compare translations/analyze techniques	0.843	0.967
Use AI for dialogue after reading	0.732	0.969

It can be seen from Table 1 that the corrected item-total correlation coefficients of all 15 items are between 0.732 and 0.869, all higher than the threshold of 0.70, indicating that each item has good discrimination and can effectively measure the corresponding construct. After deleting any single item, the Cronbach's α coefficient of the scale is still above 0.967, which proves that the composition of the scale is stable and reliable, and no item needs to be deleted or adjusted.

4.2. Validity Analysis

Construct validity analysis was carried out to test whether the scale can effectively measure the theoretical constructs it intends to measure. The KMO measure of sampling adequacy and Bartlett's test of sphericity were used for verification. The results are shown in Table 2.

Table 2. KMO and Bartlett's Test

Test Item	Value
KMO Value	0.974
Approximate χ^2	2147.750

df	105
p	< 0.001

The KMO value is 0.974, far higher than the critical standard of 0.70, indicating that the data are very suitable for factor analysis. Bartlett's test of sphericity is significant ($p < 0.001$), rejecting the null hypothesis that the correlation matrix is an identity matrix. This indicates that there is a strong correlation between variables, and the scale has good construct validity and structural stability.

4.3. Descriptive Statistics and Distribution Chart

Descriptive statistical analysis was conducted on the overall acceptance score of students, and the score distribution was visualized (Figure 1). The results showed that the overall acceptance score of college students for AI-assisted literary reading was between 3 and 4 points, showing a moderate-to-high acceptance level. Among them, the number of students with a score of 3 (neutral) accounted for 11.3%, the number of students with a score of 4 (agree) accounted for the largest proportion, reaching 39.3%, and the number of students with a score of 5 (strongly agree) accounted for 24.7%. Only a few students had a score of 1 or 2, indicating that most students hold a positive and supportive attitude toward AI-assisted literary reading.

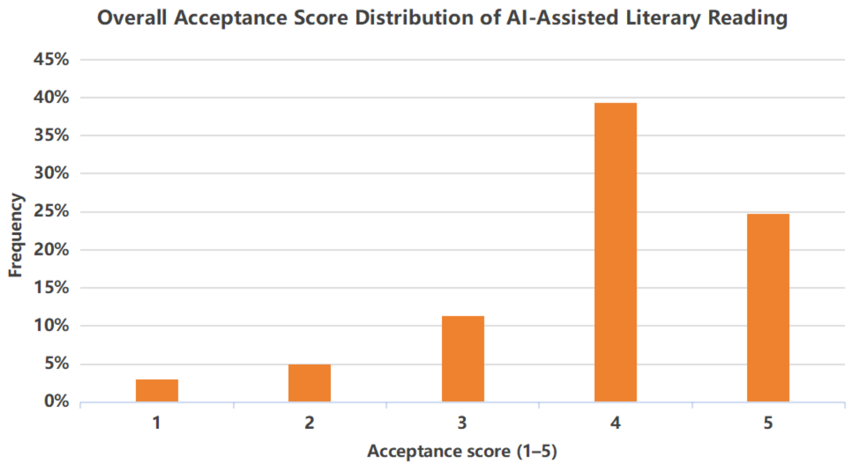

Figure 1. Overall Acceptance Score Distribution of AI-Assisted Literary Reading.

At the same time, the weekly literary reading time of the respondents was statistically analyzed (Figure 2). The results showed that 41.3% of the students spent less than 3 hours on literary reading per week, 32.7% spent 3--5 hours, 18.0% spent 6--10 hours, and only 8.0% spent more than 10 hours. This shows that most college students have limited weekly time for literary reading, which also reflects from the side that they have a realistic demand for efficient reading tools represented by AI.

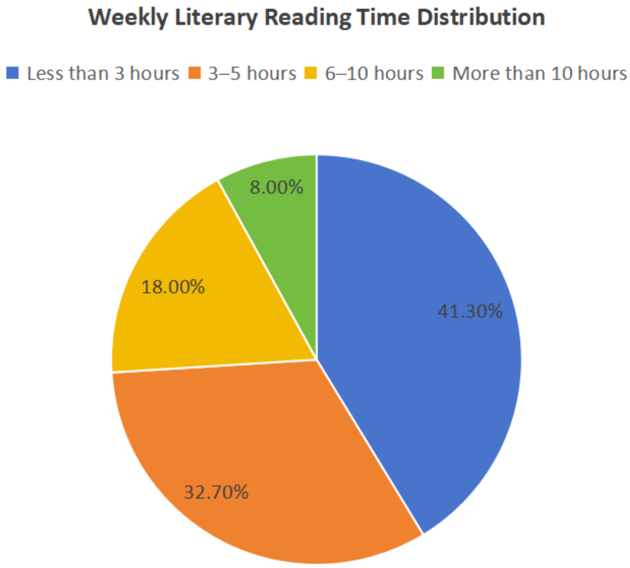

Figure 2. Weekly Literary Reading Time Distribution.

4.4. Ai Usage Scenarios (pie Chart)

The survey counted the main usage scenarios of students using AI for literary reading, and drew a pie chart to show the proportion (Figure 3). The results showed that the most frequently used scenario was sorting out complex character relationships, accounting for 28.7%, mainly for foreign classic novels such as One Hundred Years of Solitude and Chinese classical novels such as Dream of the Red Chamber; the second was explaining classical words and allusions, accounting for 24.0%, mainly for classical poetry and ancient prose; the third was supplementing historical and author background, accounting for 18.7%; followed by analyzing writing techniques (14.0%), post-reading interactive discussion (9.3%) and translation comparison (5.3%). This shows that students mainly use AI to solve basic reading comprehension difficulties, and the frequency of in-depth exploration and creative use is relatively low.

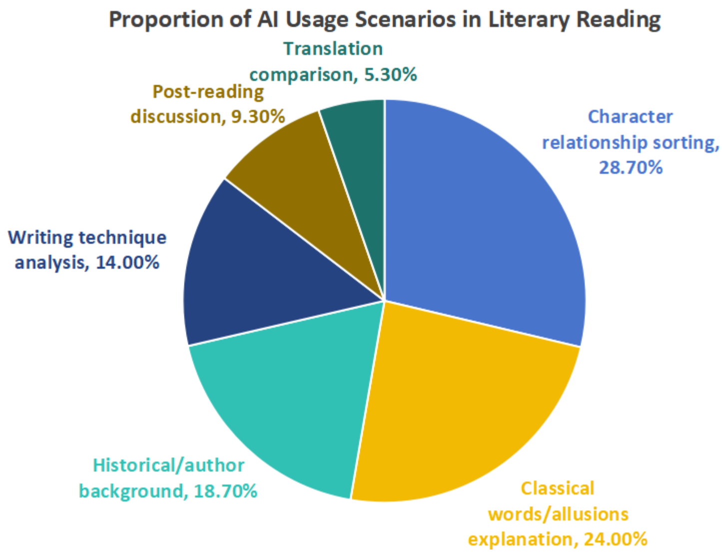

Figure 3. Proportion of AI Usage Scenarios in Literary Reading

4.5. Correlation Matrix & Heatmap

Pearson correlation analysis was conducted on the four core constructs of TAM, and the results are shown in Table 3 and Figure 4. The results showed that there was a significant positive correlation between all variables ($p < 0.01$). Among them, perceived usefulness was positively correlated with perceived ease of use ($r = 0.721$), attitude toward use ($r = 0.698$) and actual usage behavior ($r = 0.645$); perceived ease of use was positively correlated with attitude toward use ($r = 0.673$) and actual usage behavior ($r = 0.612$); attitude toward use had the strongest correlation with actual usage behavior ($r = 0.736$), indicating that the more positive the attitude, the higher the frequency of actual use.

Table 3. Correlation Matrix of Main Variables

Variable	PU	PEOU	ATU	AUB
Perceived Usefulness (PU)	1	0.721**	0.698**	0.645**
Perceived Ease of Use (PEOU)	0.721**	1	0.673**	0.612**
Attitude Toward Use (ATU)	0.698**	0.673**	1	0.736**
Actual Usage Behavior (AUB)	0.645**	0.612**	0.736**	1

$p < 0.01$; N = 150.

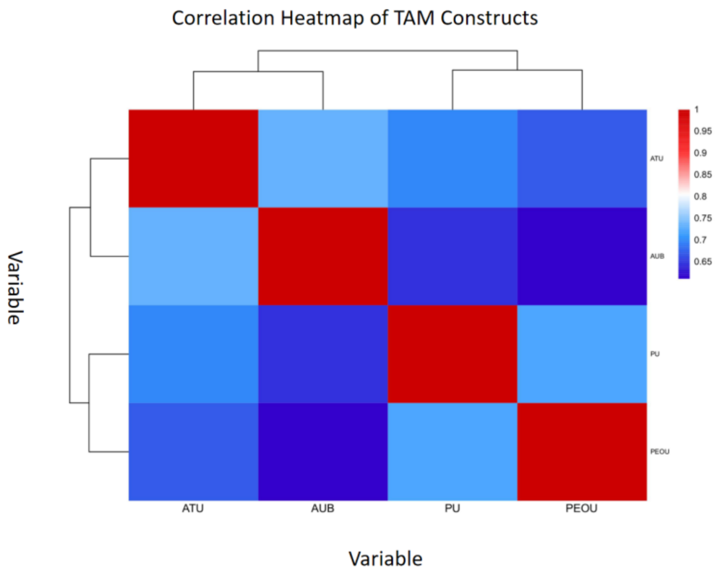

Figure 4. Correlation Heatmap of TAM Constructs.

4.6. Multiple Regression Analysis

Taking students' overall acceptance of AI-assisted literary reading as the dependent variable, correlation and regression analyses were conducted based on the constructs of the Technology Acceptance Model (TAM). The results indicate that there are certain correlations among the variables, suggesting an internal relationship between the TAM constructs. The correlation results are presented in Table 4 and Figure 5. The regression analysis was conducted as an exploratory approach to examine the potential effects of the factors on acceptance; however, as the data are exploratory in nature, the results are primarily used to illustrate the analytical method and observe general trends rather than to draw strong inferential conclusions.

Table 4. Regression Coefficients

Predictor	β	t	Sig.
AI background deepens understanding	0.255	1.828	0.070
Discussing literature with AI is interesting	0.268	1.946	0.054
(Constant)	—	17.531	0.000

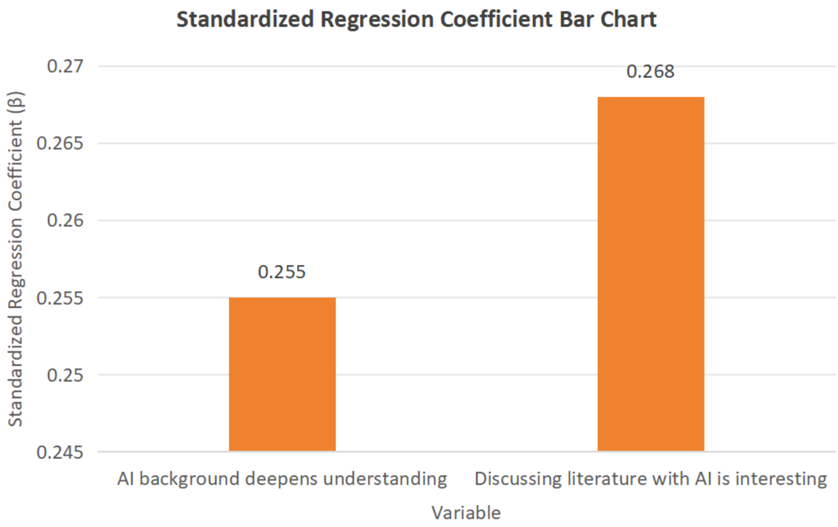

Figure 5. Standardized Regression Coefficient Bar Chart.

The regression results show that two variables are close to significant: (1) AI-provided author background and historical context can deepen students' understanding of literary texts; (2) students think it is interesting to discuss character motives, metaphors and other literary topics with AI. Basic usability items such as interface clarity and ease of query have no significant predictive effect on acceptance, indicating that students' acceptance of AI-assisted literary reading depends more on the experiential value and in-depth support added by AI than on simple functional ease of use.

4.7. Anova & S-n-k Post-hoc Test

Univariate ANOVA was used to test the differences in acceptance levels under different usage scenarios and attitude conditions. The results show that all 15 measurement items have significant main effects (all $p < 0.001$), indicating that students' acceptance varies significantly with different usage scenarios and attitudes. S-N-K post-hoc test was used for multiple comparisons, and the key results are shown in Table 5 and Figure 6.

Table 5. Between-Subjects Effects (ANOVA)

Source	Sig.
All 15 items	$p < 0.001$

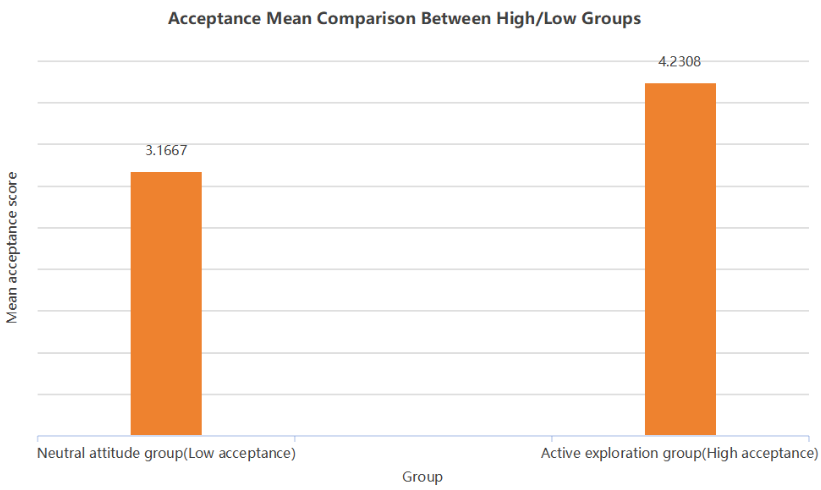

Figure 6. Acceptance Mean Comparison Between High/Low Groups

The post-hoc test results show that students with a neutral attitude toward using AI as a supplementary tool belong to the low acceptance group, with a significantly lower mean acceptance score. Students who actively try to use AI to compare different translations, analyze writing techniques and conduct in-depth exploration belong to the high acceptance group, with a significantly higher mean score. This indicates that active, positive and exploratory usage attitude and behavior are important factors that distinguish high and low acceptance levels.

4.8. Disciplinary Difference Comparison

This study further compared the differences in AI usage purposes between humanities students and STEM students, and the results are shown in Figure 7. Humanities students use AI more for in-depth interpretation, literary discussion, translation comparison and writing technique analysis, paying more attention to the aesthetic and humanistic value of reading; STEM students mainly use AI for character relationship sorting, word and allusion explanation and background query, paying more attention to solving reading obstacles and improving efficiency. This shows that disciplinary background has a significant impact on students' usage behavior and demand orientation.

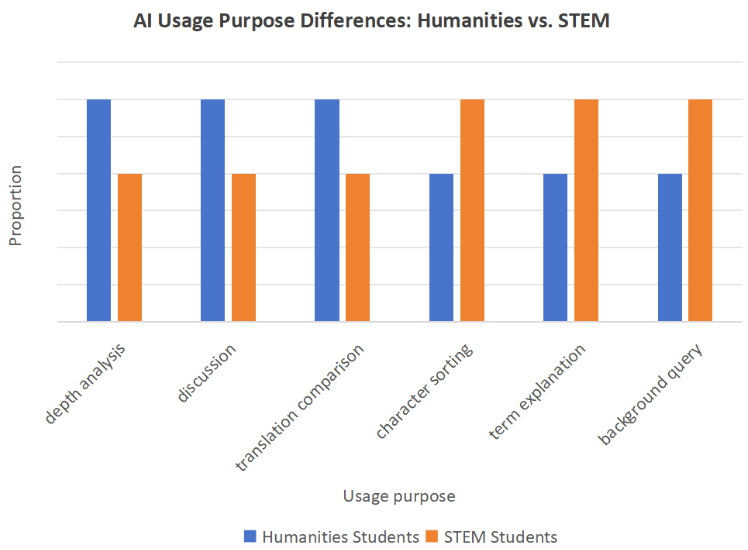

Figure 7. AI Usage Purpose Differences: Humanities vs. STEM.

4.9. Qualitative Findings

When we analyzed the open-ended responses thematically, a clear pattern emerged: students see both upsides and downsides to using AI for literary reading—they recognize its benefits but also worry about its risks. In terms of perceived benefits, students generally believe that AI can effectively lower the threshold for reading difficult literary works, quickly solve reading confusion, save time and energy, and improve reading efficiency and fluency. In terms of concerns, students mainly put forward three points: first, over-reliance on AI may lead to the loss of independent thinking ability and deep reading competence; second, AI cannot fully capture the emotional depth, literary subtlety and personalized connotation of literary works; third, AI-generated interpretation may limit students' personalized understanding and aesthetic experience, leading to homogenized thinking.

5. Discussion

5.1. Acceptance Level and Core Influencing Factors

College students in our sample were moderately to highly accepting of AI-assisted literary reading, with most willing to bring AI in as a backup tool. What really matters for acceptance, the regression analysis suggests, is not whether AI is easy to use in a basic sense, but whether it acts as an interactive discussion partner and a builder of context. The two predictors that came closest to significance—AI providing background information and AI enabling literary dialogue—point to the same conclusion: students want deep reading support, not just quick fact retrieval. Flathmann et al. have compared AI to a "navigation map" in reading—a starting point for exploration, not a final answer. Our results fit with that view [3]. Basic ease of use, meanwhile, seems to be merely a baseline requirement; it does not, by itself, drive genuine acceptance.

5.2. Active Engagement and Acceptance Differences

The ANOVA and post-hoc tests tell a clear story: students who actively and exploratively use AI show much higher acceptance, while those with a neutral attitude cluster in the low-acceptance group. This fits nicely with what Fu and colleagues call the "mirror theory"—AI acts like a mirror, amplifying the user's own abilities and mindset. Students who approach AI critically and positively can use it to see further and dig deeper; those who are passive or indifferent struggle to get much out of it. The teaching implication is important: simply giving students access to AI tools is not enough. Educators need to actively teach students how to engage with AI in an exploratory, questioning, and critical way—avoiding a passive, consumer-like mode of use [24].

5.3. Usage Scenarios and Disciplinary Differences

The scenario data show that most students turn to AI for basic reading comprehension help—sorting out who's who in a novel, understanding difficult words or allusions. Deeper, more interpretive uses are less common. At the same time, we see a clear disciplinary split: humanities students lean more on AI for close reading, comparative interpretation, and literary discussion, while STEM students focus more on efficiency—clearing up factual questions and lowering the hurdle to just getting through the text. This tells us that AI-assisted literature teaching cannot be one-size-fits-all. For humanities students, we might push toward comparative interpretation and creative dialogue; for STEM students, we might focus on lowering barriers and sparking initial interest.

5.4. Dual Experience and Educational Balance

Students in our study held two seemingly contradictory views at once: they appreciated how AI makes reading more efficient and accessible, but they also worried that leaning too much on AI might erode their own capacity for deep, independent reading. This dual response captures the ambivalence many feel toward AI-assisted literary reading. Yes, AI helps solve practical problems and opens up difficult texts. But students are also clearly aware of the risk that AI could replace, rather than support, their own reading and thinking [25]. The implication for literary education in the AI era is clear: we need to strike a balance. AI should serve as a cognitive scaffold—a helper—not a substitute for direct engagement with the text and for independent interpretation. Teachers should design activities that blend AI assistance with deep reading, protecting students' aesthetic experience and critical thinking while keeping the humanistic core of literary education intact.

5.5. Research Limitations and Future Prospects

A few caveats are in order. First, our sample is relatively small (N=150), which limits how far we can generalize. Second, the cross-sectional design gives us a snapshot, not a moving picture; we cannot see how AI-assisted reading affects students over the long term or how their habits change. Third, we only looked at college students—middle schoolers, high schoolers, and PhD researchers might behave quite differently. Future work could broaden the sample, follow students over time with longitudinal designs, and compare different age groups and cultural contexts. That would give us a much richer understanding of this area.

6. Conclusion

This study set out to understand, through a mixed-methods design and grounded in the Technology Acceptance Model (TAM), how Chinese college students accept and experience AI-assisted literary reading. Here are the main takeaways.

By and large, students are moderately to highly accepting of using AI as a supplementary tool for literary reading, and our measurement scale held up well in terms of reliability and validity. What drives acceptance, interestingly, is not basic usability—whether the interface is clear or the query is fast—but two deeper features: AI's ability to supply useful context (like author background or historical setting) and its capacity to make interactive discussion enjoyable. In other words, students want a reading companion, not just a faster search box.

We also found that how students use AI matters enormously. Those who actively explore with AI—comparing translations, testing interpretations, asking follow-up questions—show much higher acceptance than those who just use it passively or hold a neutral attitude. This finding lends empirical support to the "mirror theory" of AI in education: AI amplifies whatever the user brings to it. Disciplinary background also plays a role. Humanities students tend to lean on AI for deeper interpretation and aesthetic analysis; STEM students prefer to use it for efficiency-oriented tasks like clarifying who's who in a complex plot or explaining unfamiliar references.

Students themselves are ambivalent. They genuinely appreciate how AI lowers the barrier to difficult texts and saves time, but they also worry—often quite explicitly—about becoming over-reliant and losing their own deep-reading abilities. That ambivalence is probably healthy, and it points to a sensible middle ground: AI should be positioned as a cognitive scaffold, not a substitute for authentic literary engagement.

6.1. What's new here

This study makes a few contributions to the literature. First, it takes TAM—a model mostly used for academic or language-learning contexts—and applies it to literary reading, which is a different beast altogether, centred on aesthetic experience and personal interpretation. Unlike earlier TAM-based work on AI reading tools, which focuses on information extraction and task efficiency, we find that experiential and interactional value matter more than utilitarian ease of use. Second, by showing that active, exploratory use distinguishes high-acceptance users from low-acceptance ones, we provide empirical backing for the "mirror theory" of AI—it doesn't benefit everyone equally; it amplifies what you already bring. Third, the disciplinary contrast between humanities and STEM students challenges the one-size-fits-all approach common in AI education research. Fourth, the dual-faceted user experience—embracing efficiency while fearing cognitive atrophy—captures a nuanced ambivalence that previous work has rarely quantified.

6.2. How this compares to similar studies, and where to go next

Unlike research on AI-assisted academic reading, where perceived usefulness is often defined by speed and accuracy, our study suggests that in literary reading, usefulness is more about contextual depth and conversational enjoyment. And unlike findings in second-language writing, where perceived ease of use often predicts behavioural intention, our regression results show that basic usability items lack significant predictive power—which highlights just how different literary reading is as an affective and interpretive activity. Moreover, much of the previous discussion about AI in humanities education has been theoretical or opinion-based; our study offers empirical, mixed-methods evidence from actual student experiences.

We should be honest about what this study cannot do. The sample is small (N=150) and was recruited through convenience sampling online, so the participants may be more tech-savvy or more AI-positive than the average student. The cross-sectional design means we cannot infer causation or track long-term changes in reading habits or critical thinking. We only looked at college students; younger or older populations might differ. Self-reported usage and acceptance could be influenced by social desirability bias or faulty memory. And finally, this was done entirely in the Chinese educational context; cultural and pedagogical differences could affect how well these findings travel.

Future studies should aim for larger, more representative samples and longitudinal or quasi-experimental designs to track how reading depth, critical thinking, and AI usage evolve over time. Cross-cultural comparative work is urgently needed—how do different educational traditions and attitudes toward AI shape acceptance and use? Researchers should also test concrete intervention strategies that encourage active, exploratory, and critical AI use while preventing over-reliance (e.g., requiring students to read first, then use AI for verification or expansion, then reflect on the differences). Another promising direction is to ask how AI might be designed to preserve—or even enhance—the aesthetic and emotional dimensions of literary reading, rather than flattening them into mere information processing. Finally, more fine-grained qualitative work, such as in-depth interviews or think-aloud protocols, could shed light on the cognitive and affective processes that sit behind students' acceptance or resistance.

To sum up: this study advances both theory and practice on integrating AI into literary education. It argues for a balanced, pedagogy-driven approach—one where AI serves as a catalyst for, not a replacement of, deep reading and humanistic inquiry.

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