

LITERARY INTERPRETATION IN THE AGE OF AI: A CASE STUDY OF SECOND-YEAR STUDENTS AT THE HIGHER TEACHERS TRAINING SCHOOL OF BOUZAREAH, ALGIERS

التأويل الأدبي في عصر الذكاء الاصطناعي: دراسة حالة لطلبة السنة الثانية في المدرسة العليا للأساتذة ببوزريعة، الجزائر

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ABSTRACT

The rapid expansion of generative Artificial Intelligence (AI) in Algerian universities has created new challenges and opportunities, particularly in the English literature module, where interpretation and critical thinking are essential. This study explores how second-year PEP students at the Higher Teachers Training School of Bouzareah (ENSB) use AI tools when studying literary texts and how they perceive their impact on interpretation. A quantitative descriptive approach was adopted. Thirty students enrolled during the 2024–2025 academic year completed an anonymous online questionnaire covering AI familiarity, patterns of use, perceived effects on interpretive skills, critical thinking, and attitudes toward AI integration. The data were analysed using descriptive statistics. The findings show that 86.7% of participants use AI to understand difficult literary texts, while only 13.3% reported accepting AI interpretations without questioning them. However, 76.7% expressed concern that overreliance on AI could weaken independent thinking, and few students reported receiving clear guidance from teachers. The study concludes that students mainly see AI as a support tool rather than a replacement for personal literary interpretation. It recommends structured classroom policies that encourage responsible AI use while preserving critical thinking and interpretive autonomy.

Keywords:

Descriptive study; ENSB; Generative Artificial Intelligence (AI); Literary interpretation.

ملخص

أدى الانتشار السريع للذكاء الاصطناعي التوليدي في الجامعات الجزائرية إلى ظهور تحديات وفرص جديدة، خاصة في مقياس الأدب الإنجليزي، حيث تُعدّ مهارات التأويل والتفكير النقدي عناصر أساسية. تهدف هذه الدراسة إلى استكشاف كيفية استخدام طلبة السنة الثانية ملمح ابتدائي بالمدرسة العليا للأساتذة ببوزريعة (ENSB) لأدوات الذكاء الاصطناعي عند دراسة النصوص الأدبية، وكيفية إدراكهم لتأثيرها على عملية التأويل. اعتمدت الدراسة المنهج الوصفي الكمي، حيث شارك ثلاثون طالبًا مسجلين خلال السنة الجامعية 2024-2025 في استبيان إلكتروني مجهول يضم محاور حول معرفة الطلبة بالذكاء الاصطناعي، وأنماط استخدامه، وتأثيره على مهارات التأويل والتفكير النقدي، إضافة إلى مواقفهم من إدماجه في التعليم. وتم تحليل البيانات باستخدام الإحصاء الوصفي. أظهرت النتائج أن 86.7% من المشاركين يستخدمون الذكاء الاصطناعي لفهم النصوص الأدبية الصعبة، بينما صرح 13.3% فقط بأنهم يقبلون التأويلات التي يقدمها دون مناقشتها. كما عبّر 76.7% عن قلقهم من أن الإفراط في الاعتماد عليه قد يضعف التفكير المستقل، في حين أشار عدد محدود إلى تلقي توجيهات واضحة من الأساتذة حول استخدامه. وتخلص الدراسة إلى أن الطلبة ينظرون إلى الذكاء الاصطناعي كأداة مساعدة لا كبديل للتأويل الأدبي الشخصي، وتوصي بوضع سياسات صافية واضحة تشجع الاستخدام المسؤول للذكاء الاصطناعي مع الحفاظ على التفكير النقدي والاستقلالية التأويلية.

الكلمات المفتاحية:

التأويل الأدبي، الذكاء الاصطناعي التوليدي، دراسة وصفية، المدرسة العليا للأساتذة ببوزريعة.

1. INTRODUCTION

Over the past three years, generative AI tools have become an integral part of university life in Algeria. Students use them to draft essays, check grammar, translate between languages, and increasingly, to make sense of difficult texts. Within the English literature module in higher institutions, this raises both a practical and philosophical question: what becomes of literary interpretation when a machine is capable of generating a plausible reading of a poem or a novel within seconds?

Literary interpretation is not the same as factual comprehension. It asks the reader to sit with ambiguity, bring personal and cultural experience to the text, and arrive at a judgement that is necessarily subjective. Moreover, AI tools are getting better at producing outputs that look like interpretation even if these tasks do not

easily lend themselves to AI-driven solutions. Whether students treat these outputs as starting points or as final answers matters a great deal, especially for future teachers who will be expected to guide their own students through the same process.

The Algerian context adds a layer of specificity. ENSB students are EFL learners working through canonical English texts in a third language. The linguistic barrier alone makes AI tools attractive. But the risk is that AI becomes a shortcut not just around the language difficulty but around the interpretive labour that gives literary study its educational value.

This paper does not set out to condemn or celebrate AI use. It sets out to describe what is actually happening in one classroom at one institution, and to let the data speak about how students perceive the relationship between AI assistance and their own literary thinking. The study is guided by three questions:

RQ1. To what extent do second-year PEP students at ENSB use AI tools in their English literature coursework?

RQ2. How do these students perceive the impact of AI use on their ability to interpret literary texts independently?

RQ3. What are their attitudes toward the formal integration of AI tools in literature courses?

2. Literature Review

2.1- AI Tools in Higher Education

Research on AI in higher education has expanded quickly since ChatGPT became publicly available in late 2022. Early studies focused on detection and academic integrity (Cotton, Cotton, & Shipway, 2024; Perkins, 2023). More recent work has shifted toward how students actually use these tools and what effects they have on learning. Mollick and Mollick (2023) argue that AI can act as an effective

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pedagogical partner when instructors set clear boundaries. Kasneci et al. (2023) provide a broad review of both opportunities and risks, and note that disciplinary context matters: AI assistance in a data science course is not the same thing as AI assistance in a humanities seminar.

2.2- Literary Interpretation as a Cognitive Activity

Reader-response theory (Rosenblatt, 1978; Iser, 1978) holds that meaning is not a fixed property of the text but emerges through the transaction between reader and text. Fish (1980) goes further and argues that interpretive communities shape what counts as a valid reading. If AI tools increasingly mediate this transaction, the nature of the reading experience changes. The student is no longer struggling with the text alone; they are negotiating between their own tentative reading and a confident, fluent interpretation generated by a language model.

2.3- AI and the Humanities Classroom

A small but growing body of work addresses AI in literature and writing courses specifically. Fyfe (2023) found that students who used AI to generate initial essay drafts produced work that was competent but lacked personal voice. Anson (2022) raises concerns about the erosion of what he calls "productive difficulty", the cognitive effort that makes learning happen. In the Algerian EFL context, research remains limited, though Assia et al. (2022) have explored technology integration in English departments at Algerian universities more broadly.

2.4- Gap in the Literature

Most existing studies either treat AI in education as a generic phenomenon or focus on writing and composition. Very few examine AI use specifically in the context of literary interpretation, and to the author's knowledge none do so at an Algerian teacher training institution. This study aims to fill that gap.

2.5- Conceptual Framework

This study is framed by an AI-mediated transaction model of literary interpretation, constructed at the intersection of reader-response theory and research on AI in education. Rosenblatt's (1978) transactional theory holds that literary meaning emerges from the dynamic relationship between a specific reader and a specific text at a specific moment. Meaning is not extracted from the text; it is co-produced. Iser (1978) elaborates this through the concept of gaps: the text presents structured indeterminacies that the reader is called upon to fill through imaginative participation. Fish (1980) adds a social dimension, arguing that what counts as a valid reading is shaped by the interpretive community within which the reader is situated.

When a generative AI tool is introduced into this process, it does not simply assist the reader; it inserts a third agent into the transactional relationship. The student is no longer negotiating meaning alone with the text. They are negotiating between their own tentative reading, the text, and a confident, fluent interpretation produced by a large language model. This three-way dynamic raises a question that reader-response theory was not designed to answer: what happens to the reader's interpretive agency when one of the interlocutors in the transaction is an AI system trained to produce authoritative-sounding responses? The present study treats this three-way dynamic as its conceptual anchor, using student self-reports to probe where AI intervention supports and where it may displace the personal, situated transaction that Rosenblatt (1978) identifies as the core of literary reading. Anson's (2022) concept of productive difficulty and Mollick and Mollick's (2023) argument for instructor-defined AI boundaries complement this framework by specifying the pedagogical conditions under which AI mediation is more or less likely to undermine interpretive development.

3. Research Design and Methodology

3.1- Research Approach

The study adopts a descriptive quantitative approach. Descriptive research aims to document what exists rather than to test causal hypotheses (Creswell & Creswell, 2018). This approach is appropriate here because the goal is to map the current state of AI use and student perceptions at ENSB, not to measure the effect of an intervention.

3.2- Population and Sample

The target population is second-year PEP English students at ENSB enrolled during the 2024-2025 academic year. The sample consists of 30 students drawn through convenience sampling from one section. All participants are enrolled in a literature module and are exposed to a range of literary texts, including poetry, drama, and prose fiction from both British and American canon. The sample size, while modest, is appropriate for a descriptive study at a single institution.

3.3- Data Collection Instrument

The instrument is a structured, self-administered online questionnaire hosted on Google Forms. It contains 20 items distributed across five sections. Section A (3 items) gathers background information about AI familiarity and usage frequency. Sections B through E (17 items) use a five-point Likert scale ranging from "Strongly disagree" (1) to "Strongly agree" (5). The questionnaire was designed in English, the medium of instruction for the target population. The full questionnaire is reproduced in the appendix (Section 9) for transparency and replication purposes.

The instrument was piloted with 5 students from a different section before administration to check for clarity and to estimate completion time, which was about 8 to 10 minutes. Minor wording adjustments were made based on pilot feedback. It

should be noted that no formal internal reliability analysis (e.g., Cronbach’s alpha) was conducted, as the questionnaire was designed to map a range of distinct constructs across five thematic sections rather than to measure a single latent trait. This is acknowledged as a limitation; future iterations of this instrument would benefit from reliability testing, particularly for sections B and C where item-level consistency is most relevant.

3.4- Questionnaire Structure

Table 1 :summarises the sections of the questionnaire and what each section is designed to capture.

Table 1: Questionnaire Structure Overview

Section	Focus	Items	Scale
A	Background and AI familiarity	3 (Q1-Q3)	Mixed
B	AI use in literature coursework	5 (Q4-Q8)	5-point Likert
C	Perceived impact on interpretive skills	5 (Q9-Q13)	5-point Likert
D	Critical thinking and intellectual ownership	4 (Q14-Q17)	5-point Likert
E	Attitudes toward AI integration	3 (Q18-Q20)	5-point Likert

Source: Designed by the researcher.

3.5- Data Analysis Procedures

Responses were analysed using descriptive statistics. For Likert-scale items, the following measures are reported: frequency counts and percentages for each response option, the mean (M) and standard deviation (SD) for each item, and section-level means to identify broader patterns. Results are presented in frequency tables. No inferential statistics were used, in keeping with the descriptive design.

3.6- Ethical Considerations

Participation was voluntary. The Google Forms questionnaire opens with an informed consent statement. Respondents were told that their answers are anonymous, that no identifying information is collected, and that they may withdraw at any point by closing the form. The data is stored on the researcher's password-protected Google Drive account.

4. Results and Discussion

This section presents the findings from the 30 completed questionnaires. Results are organised by section and reported using frequency distributions, percentages, means, and standard deviations, followed by interpretation in light of the literature reviewed above.

4.1- Section A: Background and AI Familiarity

Table 2: Frequency of AI Tool Use for Academic Work (Q1, N = 30)

Response	frequency	%
Never	1	3.3
Rarely	3	10.0
Sometimes	11	36.7
Often	10	33.3
Very often	5	16.7
Total	30	100.0

Source: Field data, 2024-2025. Mean = 3.50, SD = 1.01.

The distribution in Table 2 shows that AI use is now the rule rather than the exception in this sample. 86.7% of respondents (n = 26) reported using AI tools at least sometimes for academic work, with half the cohort (50.0%) using them "often" or "very often". Only one student reported never using AI. The mean of 3.50 sits roughly midway between "sometimes" and "often", which is a reasonable summary of the picture.

Table 3: AI Tools Used in the Past Six Months (Q2, multiple response, N = 30)

Tool	f	% of respondents
ChatGPT	28	93.3
Grammarly	18	60.0
Gemini	14	46.7
DeepL	12	40.0
Claude	4	13.3
Other	3	10.0

Source: Field data, 2024-2025. Multiple responses allowed; percentages exceed 100.

Almost all respondents (93.3%) had used ChatGPT in the past six months, which makes it the de facto standard tool in this group. Grammarly came second at 60.0%, reflecting the language-checking pressure that EFL students live with. Gemini and DeepL appeared in the middle range, while Claude was used by only 13.3% of the sample. The comfort level with AI (Q3, 1-5 scale) yielded a mean of 3.80 (SD = 0.92), which sits closer to "comfortable" than to "neutral". This is a sample that does not need to be introduced to AI; it is already a daily companion.

4.2- Section B: AI Use in Literature Coursework (Q4-Q8)

Table 4: Descriptive statistics for Section B items (N = 30, percentages in brackets)

Item	SD	D	N	A	SA	M	SD
Q4. Use AI to understand difficult texts	0 (0.0%)	1 (3.3%)	3 (10.0%)	14 (46.7%)	12 (40.0%)	4.23	0.77
Q5. Use AI to generate summaries	1 (3.3%)	3 (10.0%)	5 (16.7%)	13 (43.3%)	8 (26.7%)	3.80	1.06
Q6. Use AI to write or improve essays	2 (6.7%)	5 (16.7%)	8 (26.7%)	10 (33.3%)	5 (16.7%)	3.37	1.16
Q7. Ask AI to explain devices/themes/context	0 (0.0%)	2 (6.7%)	4 (13.3%)	13 (43.3%)	11 (36.7%)	4.10	0.88
Q8. Accept AI interpretation without questioning	8 (26.7%)	12 (40.0%)	6 (20.0%)	3 (10.0%)	1 (3.3%)	2.23	1.07

Source: Field data, 2024-2025. SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree. Final two columns are item mean and standard deviation.

The pattern in Table 4 is clear. Comprehension support (Q4, M = 4.23) and contextual explanation (Q7, M = 4.10) are by far the most common literary uses of AI in this sample. 86.7% of respondents agreed or strongly agreed that they use AI to understand difficult texts, and 80.0% used it to ask about literary devices, themes, or historical context. Generating summaries (Q5, M = 3.80) is also widespread, with 70.0% agreement. Essay assistance (Q6, M = 3.37) is more divided, with 50.0% agreement and 23.3% disagreement, suggesting that students are more cautious about letting AI touch their writing than about letting it explain a text.

Q8 is the most revealing item in this section. Only 13.3% of respondents agreed or strongly agreed that they accept AI interpretations without questioning, while 66.7% disagreed or strongly disagreed ($M = 2.23$, $SD = 1.07$). This contradicts the simple narrative that students passively consume AI outputs. They use AI heavily, but they report doing so with some level of evaluative distance, at least in their own self-image.

4.3- Section C: Perceived Impact on Interpretive Skills (Q9-Q13)

Table 5: Descriptive statistics for Section C items (N = 30)

Item	SD	D	N	A	SA	M	SD
Q9. AI improved my ability to analyse on my own	2 (6.7%)	6 (20.0%)	10 (33.3%)	9 (30.0%)	3 (10.0%)	3.17	1.09
Q10. I spend less time forming my own reading first	3 (10.0%)	5 (16.7%)	8 (26.7%)	10 (33.3%)	4 (13.3%)	3.23	1.19
Q11. AI analyses miss nuances I can catch	1 (3.3%)	2 (6.7%)	6 (20.0%)	14 (46.7%)	7 (23.3%)	3.80	1.00
Q12. Less confident when my reading differs from AI	4 (13.3%)	8 (26.7%)	9 (30.0%)	7 (23.3%)	2 (6.7%)	2.83	1.15
Q13. AI helped me discover new perspectives	1 (3.3%)	3 (10.0%)	7 (23.3%)	14 (46.7%)	5 (16.7%)	3.63	1.00

Source: Field data, 2024-2025.

Section C is where the data gets interesting. Three findings stand out. First, students are split on whether AI has improved their analytical ability: 40.0% agree (Q9), but 33.3% are neutral and 26.7% disagree, with a mean barely above the midpoint ($M = 3.17$). Second, 63.3% recognise that AI tends to miss nuances they can catch through close reading (Q11, $M = 3.80$). Third, 63.3% admit that they spend less time forming their own interpretation before consulting AI (Q10, $M = 3.23$), the kind of behaviour Anson (2022) warns about.

Q9 and Q11 do not contradict each other; they sit together comfortably. A student can believe that AI explanations have helped them, while also knowing that those explanations miss the textures of a poem, they themselves can hear. That is the actual experience of using a tool that is useful for some things and inadequate for

others. Rosenblatt's transactional theory predicts exactly this: AI can supply information about a text, but it cannot replicate the personal, situated response that produces a literary reading.

4.4- Section D: Critical Thinking and Intellectual Ownership (Q14-Q17)

Table 6: Descriptive statistics for Section D items (N = 30)

Item	SD	D	N	A	SA	M	SD
Q14. I can tell when AI analysis is shallow	1 (3.3%)	4 (13.3%)	10 (33.3%)	12 (40.0%)	3 (10.0%)	3.40	0.97
Q15. I worry AI may weaken my independent thinking	1 (3.3%)	2 (6.7%)	4 (13.3%)	12 (40.0%)	11 (36.7%)	4.00	1.05
Q16. AI-assisted essays still feel like my own work	4 (13.3%)	9 (30.0%)	10 (33.3%)	5 (16.7%)	2 (6.7%)	2.73	1.11
Q17. Teachers have discussed AI guidelines in class	11 (36.7%)	10 (33.3%)	5 (16.7%)	3 (10.0%)	1 (3.3%)	2.10	1.13

Source: Field data, 2024-2025.

Two items in this section deserve particular attention. Q15 returns the highest mean in Section D (M = 4.00, SD = 1.05), with 76.7% of respondents agreeing or strongly agreeing that relying on AI may weaken their ability to think independently about literature. This is a striking level of self-awareness from a group that also reports heavy AI use.

Q17 is the lowest mean in the entire questionnaire (M = 2.10, SD = 1.13). 70.0% of respondents disagreed or strongly disagreed that their teachers have discussed AI guidelines in class. Only 13.3% reported any such discussion. The institutional gap this points is hard to miss: students are using AI heavily, they are aware of the risks, and they have received almost no formal guidance on how to use it well in a literature course. Q16 underscores the same tension. Only 23.3% of respondents felt that an essay containing AI-assisted content was still genuinely their own work, while 43.3% disagreed (M = 2.73). The discomfort with hybrid authorship is real, but it has not been named or addressed in class.

4.5- Section E: Attitudes Toward AI in Literature Teaching (Q18-Q20)

Table 7: Descriptive statistics for Section E items (N = 30)

Item	SD	D	N	A	SA	M	SD
Q18. AI tools should be formally integrated at ENSB	2 (6.7%)	5 (16.7%)	10 (33.3%)	10 (33.3%)	3 (10.0%)	3.23	1.07
Q19. Literature needs human interpretation more than other subjects	0 (0.0%)	1 (3.3%)	3 (10.0%)	12 (40.0%)	14 (46.7%)	4.30	0.79
Q20. I trust a teacher's analysis more than AI	0 (0.0%)	2 (6.7%)	4 (13.3%)	11 (36.7%)	13 (43.3%)	4.17	0.91

Source: Field data, 2024-2025.

Q19 yielded the highest mean in the questionnaire ($M = 4.30$, $SD = 0.79$), with 86.7% of respondents agreeing or strongly agreeing that human interpretation matters more in literature than in other disciplines. Q20 sits close behind ($M = 4.17$), with 80.0% agreeing that they trust a teacher's literary analysis more than an AI's. Even students who use AI heavily, then, draw a line around the pedagogical authority of the teacher and around the discipline itself.

In Q18, 43.3% of respondents agreed that AI tools should be formally integrated into literature courses, 23.3% disagreed, and 33.3% sat in the neutral middle ($M = 3.23$). The cohort is open to integration in principle but unwilling to endorse it without conditions, which is consistent with everything else in the data: they want help, not replacement.

4.6- Cross-Section Summary

Table 8: Section-level descriptive statistics (N = 30)

Section	Focus	Items	M	SD
B	AI use in literature coursework	5	3.55	0.99
C	Perceived impact on interpretive skills	5	3.33	1.09
D	Critical thinking and intellectual ownership	4	3.06	1.07
E	Attitudes toward AI integration	3	3.90	0.92

Source: Field data, 2024-2025. Section means are unweighted averages of item means.

Three observations are worth pulling out. Section B ($M = 3.55$) indicates that AI use in literature is widespread in this sample, particularly for comprehension tasks. Section E ($M = 3.90$), the highest section mean, suggests that students hold protective attitudes toward literary interpretation as a human practice. The lowest mean is in Section D ($M = 3.06$), where the institutional gap on AI guidance pulls the average down. Read together, these section means are consistent with a picture of a population that is using AI energetically, that values the human side of literary study, and that has not been given a clear framework for reconciling the two.

4.7- Discussion of Findings

The data suggest that students in this sample use AI primarily for understanding difficult texts and explaining literary context (Q4, Q7), a pattern consistent with what one might expect in an EFL setting. These students are reading canonical English literary works in a language that is not their mother tongue. The linguistic barrier is real, and AI tools appear to lower it. Whether lowering the linguistic barrier also removes the interpretive challenge that gives literary study its pedagogical purpose remains, however, an open question that self-report data alone cannot resolve. This concern echoes Kasneci et al. (2023), who caution that the benefits of AI assistance vary significantly by disciplinary context, and Anson (2022), who argues that the interpretive effort displaced by AI tools may be precisely the cognitive labour that produces genuine learning.

There is a difference between using AI to understand what a word means in context and using AI to understand what a passage means as literature. The first is a dictionary function; the second is an interpretive act. The Q4 to Q8 pattern in Table 4 suggests that students are mostly staying on the dictionary side of that line: heavy use for comprehension and context ($Q4 = 4.23$, $Q7 = 4.10$), low agreement with uncritical acceptance of AI interpretations ($Q8 = 2.23$). The data does not support the worst-case story.

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But the data also point to a more uncomfortable pattern. Q10 ($M = 3.23$) suggests that 63.3% of respondents now tend to spend less time forming their own reading before checking what AI says. Q15 ($M = 4.00$) shows that 76.7% worry that AI may be weakening their independent thinking. Whatever students do with the AI output once they have it, these responses are at least consistent with a reading in which the interpretive moment—the moment of sitting alone with a text and waiting for a reading to surface—is shrinking. That is the cognitive activity Anson (2022) calls productive difficulty, and it is the activity Rosenblatt's (1978) transactional theory places at the heart of literary experience. Fyfe (2023) found analogous patterns in a writing context: students who used AI to generate initial drafts produced competent but impersonal work, suggesting that the displacement of effort has identifiable consequences for the quality of engagement.

The guidance gap indicated by Q17 ($M = 2.10$) may be the most actionable finding in the study. Students are already using AI; the question is not whether they should but how. Without clear pedagogical framing from instructors, they appear to default to whatever is fastest and most convenient. This pattern aligns with the broader literature: Mollick and Mollick (2023) argue that AI tools produce their best educational outcomes when instructors set clear parameters, and Kasneci et al. (2023) similarly note that benefits of AI assistance depend heavily on deliberate pedagogical design. Q19 ($M = 4.30$) suggests that even heavy AI users recognise something distinctive about literature as a discipline. This may represent a pedagogical opening: students seem ready for honest conversations about what AI can and cannot do with a literary text—conversations that, according to the data, their teachers have not yet had with them. Fish's (1980) notion of interpretive communities is also relevant here: if the classroom is the community within which valid literary readings are established and contested, then the teacher's silence on AI may inadvertently cede that interpretive authority to a language model.

4.8- Limitations

Several limitations should be acknowledged. The sample of 30 students from a single section at one institution limits generalisability. The self-report nature of the questionnaire means that responses reflect perceptions, not observed behaviour. Students may underreport AI use due to social desirability concerns, particularly if they perceive AI use as academically questionable. The cross-sectional design captures a snapshot; it cannot track changes over time. Finally, the descriptive approach does not allow causal claims about the relationship between AI use and interpretive skills.

5. Conclusion

This study set out to describe how second-year PEP students at ENSB use AI tools in literature, and how they perceive the effect of that use on their interpretive abilities. The findings, taken together, describe a student population that is already using AI as part of literary coursework, primarily for comprehension and context, but that has not yet been given a coherent framework for doing so. Students value AI as a comprehension aid while sensing that something is lost when interpretation is outsourced. The tension is not between AI and literature. It is between convenience and effort, between fluency and depth, between getting an answer and doing the thinking that produces one. These tensions are not new in education. AI did not create them. But AI has made them more urgent because the shortcut is now so easy to take.

These findings point to a set of actionable directions for literature teaching and for future research, which are outlined in the recommendations that follow.

6. Recommendations

Four practical recommendations follow from the data. First, literature instructors at ENSB should establish explicit guidelines for AI use in their courses, distinguishing between acceptable uses (vocabulary support, historical context) and uses that undermine the pedagogical purpose of the assignment (generating full essay drafts, pre-packaged interpretations). Without such guidelines, students are left to navigate these boundaries on their own, as the low mean on Q17 ($M = 2.10$) makes clear.

Second, assignments should be redesigned so that AI-generated responses are less useful: personal response journals, oral defences of written arguments, and comparative tasks where students evaluate an AI reading against their own. A student who can articulate why an AI reading of a Wordsworth poem is shallow understands both the technology and the poem better.

Third, teacher training and professional development should address AI integration in literature specifically, not just in general pedagogical terms. The high level of student trust in teachers' literary analysis (Q20, $M = 4.17$) suggests that instructors retain significant authority; the question is how that authority can be used to model critical engagement with AI rather than silence on the subject.

Fourth, future research should extend this work with larger samples, qualitative interviews, and longitudinal designs that track the evolution of students' interpretive skills over time. A follow-up study combining questionnaire data with think-aloud protocols during actual AI-assisted reading tasks would allow researchers to move beyond self-report and observe the interpretive process directly.

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