Same Tools, Different Needs: AI-Assisted Reading of Scientific and Technological English among English-Major and Engineering Students

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ABSTRACT

This study examines how AI tools support the reading of scientific and technological English materials, comparing English-major and engineering students at the International Training Faculty, Thai Nguyen University of Technology. As generative AI has become a routine part of academic reading, the question arises whether learners from different disciplinary backgrounds use these tools in the same way. A cross-sectional comparative survey was administered to 88 undergraduate students (33 English majors and 55 engineering students). The questionnaire covered background characteristics, reported reading difficulties, purposes of AI use, tools used, and perceived support and challenges. Data were analysed using descriptive statistics, multiple-response analysis, chi-square tests of independence with Fisher's exact test, and the phi coefficient. Tool selection did not differ significantly between the two groups: ChatGPT was dominant in both (87.5% overall), and no participant reported using DeepL or QuillBot. Reported difficulties and purposes, however, diverged sharply. Specialised vocabulary was the principal barrier for English majors (60.6% versus 10.9%, $\varphi = .53$), whereas engineering students reported greater difficulty with technical concepts (74.5% versus 33.3%, $\varphi = .41$), complex sentence structures, and scientific background knowledge. These profiles were mirrored in AI use: 66.7% of English majors used AI to interpret specialised vocabulary against 10.9% of engineering students ($\varphi = .58$), while 83.6% of engineering students used it to clarify technical concepts against 27.3% of English majors ($\varphi = .56$). In both groups, higher-order purposes such as summarising, checking comprehension, and analysing text structure were rare. The findings indicate that disciplinary background shapes how students use AI rather than which tool they select, and support differentiated guidance in ESP reading instruction.

Keywords: AI-assisted reading; English for Specific Purposes; scientific and technological English; disciplinary differences; Vietnamese EFL learners

INTRODUCTION

As higher education becomes increasingly internationalised and digitalised, the ability to read scientific and technological texts in English has become a basic requirement for students. Specialised textbooks, research articles, technical reports, and product documentation are published predominantly in English, particularly in science and engineering. Comprehending such material, however, involves considerably more than recognising individual words or translating sentences one by one. These texts are characterised by high information density, dense academic terminology, complex grammatical structures, and concepts that require readers to draw on prior background knowledge (Grabe & Stoller, 2020; Sanz-Tejeda et al., 2026). Students may therefore encounter substantial difficulty even when they already possess a reasonable level of general English proficiency.

The sources of that difficulty vary from reader to reader. For some learners the obstacles are primarily linguistic, involving specialised vocabulary, sentence structure, and academic register. For others they arise from insufficient background knowledge or unfamiliarity with the technical concepts under discussion. Kintsch (1998) argued that reading is not merely the processing of information presented on the page but depends on the reader's capacity to connect new information with existing knowledge. This is particularly consequential for scientific and technological texts, whose authors typically assume that readers already command a certain level of domain knowledge. The same text may thus pose quite different problems to readers with differing levels of specialised knowledge.

The rapid development of AI, and of generative systems such as ChatGPT in particular, has created new possibilities for resolving these difficulties. Rather than consulting a conventional dictionary or translation tool, students can ask an AI system to explain a term, paraphrase a sentence in simpler language, illustrate a concept, supply examples, or summarise a passage. Recent studies report that AI can support English reading, vocabulary development, and learner autonomy while helping learners overcome obstacles encountered during reading (Dinh et al., 2024; El Hassan & Alsalwah, 2025; Ironsi & Bostanci, 2026). Other work suggests that AI can also facilitate higher-order reading activities such as generating questions, synthesising information, and verifying comprehension (Thongsan & Anderson, 2025; Zhang et al., 2025). The effectiveness of these tools, however, depends not only on their capabilities but on the learner's purpose and manner of use.

Although research on AI in English language learning is expanding rapidly, relatively little is known about how learners from different disciplinary backgrounds use these tools. Existing studies have tended to examine either EFL learners and English majors or students in science and engineering fields, but rarely both within a single design. This gap matters because the two groups bring complementary strengths and weaknesses to the same task: English majors typically command stronger language resources but limited domain knowledge, whereas engineering students possess domain knowledge but may struggle with dense academic English.

The present study therefore examines how AI supports the reading of scientific and technological English among English-major and engineering students at Internationl Training Faculty, Thai Nguyen University of Technology. It investigates the tools students use, the reading difficulties they report, and the purposes for which they turn to AI. Two research questions guide the study:

(1) What AI tools do English-major and engineering students use when reading scientific and technological English materials, and what reading difficulties do they report?

(2) How do the two groups differ in their purposes for using AI, and what do these differences reveal about the nature of their reading barriers?

By examining both groups within a single setting, the study aims to establish whether AI is being used to meet similar or divergent needs, and to provide empirical grounding for more differentiated approaches to integrating AI into the teaching of scientific and technological English.

LITERATURE REVIEW

AI in Education and English Language Learning

AI is shifting from a supporting technology to an integral component of the teaching and learning environment. In language education it can provide immediate feedback, personalise content, explain linguistic features, and create opportunities for interaction. Tang and Zhang (2026) show that research on AI in EFL contexts has expanded rapidly, encompassing a wide range of tools, skills, and outcomes.

Two recent systematic reviews reach convergent conclusions. Deng and Jamaludin (2026) synthesise the roles generative AI has come to play across EFL instruction, while Uygun and Demir (2026), reviewing studies published between 2023 and 2025, document the rapid expansion of AI applications in English as a foreign and second language education. Both reviews indicate that research attention has concentrated on writing and speaking, with reading receiving comparatively less empirical scrutiny.

One of the principal advantages of AI lies in the immediacy of the feedback it offers. Instead of consulting dictionaries or translation tools, learners can ask an AI system to explain a word, rephrase a sentence, supply examples, or clarify an ambiguous passage. This interactive capacity allows AI to function as a personalised form of learning support.

Research on the acceptance of AI in the Vietnamese context also indicates growing interest. Drawing on the Technology Acceptance Model and UTAUT, Thao (2025) examined the factors shaping university students' decisions to use generative AI for English learning and found that perceptions of the technology, its perceived usefulness, and the learning process itself all influenced adoption. Research on AI in education must therefore account not only for the affordances of the technology but for how students perceive and deploy it.

AI-Supported Reading Comprehension

Reading comprehension is a domain in which AI can be particularly useful, since reading routinely generates local difficulties requiring resolution, whether at the level of a word, a sentence, an idea, or an entire paragraph. El Hassan and Alsalwah (2025) found that ChatGPT supported both reading comprehension and vocabulary development in EFL classrooms. In the Vietnamese context, Dinh, Do, and Tran (2024) examined the effects of chatbots on EFL students' reading comprehension, critical thinking, and learner autonomy.

Other studies have examined self-regulation and interaction more closely. Sagita, Sagita, and Syafari (2025) found that generative AI support encouraged the use of self-regulated reading strategies and increased EFL students' interest in reading. Supardan and Capati (2026) characterise AI as a mirror through which students can monitor their own comprehension and address difficulties as they read. Thongsan and Anderson (2025) used ChatGPT to develop reading skills by prompting learners to examine arguments, identify bias, and synthesise information. Taken together, these studies indicate that AI need not function merely as a device for translating or explaining meaning; used appropriately, it can support higher-order thinking and metacognitive awareness.

Challenges in Reading Scientific and Technological English

Despite this potential, reading technical texts presents distinctive challenges. First, specialised terms often carry meanings that diverge from general English and cannot reliably be inferred from context. Second, scientific texts favour long sentences, embedded clauses, nominalisation, and the passive voice. Third, readers require background knowledge in order to grasp concepts and the relations among them.

A study of the reading difficulties faced by Indonesian EFL students found that learners struggled to locate specific details, identify contrasting ideas, and recognise topic sentences, and that they turned to AI as a form of support (Harida et al., 2025). Alshakhi (2025) similarly reports that adult EFL learners find it difficult to read at speed while maintaining comprehension, and proposes AI as a possible means of support.

These challenges are not uniform across learner groups. English majors may bring a stronger linguistic foundation but limited specialised knowledge, whereas engineering students may know their field well yet struggle with dense academic English. This asymmetry motivates the present study's comparison of the two groups.

AI in English for Specific Purposes

English for Specific Purposes differs from General English in that the language is tailored to a particular discipline or occupation. The application of AI in ESP is therefore of considerable relevance to fields such as engineering, medicine, aviation, and business. Boeru (2024) argues that AI can be used in ESP to address learner needs and to support engagement with specialised content.

Enamorado (2025) examined 91 university students studying English for Tourism Purposes and found that ChatGPT supported reading comprehension, vocabulary learning, role-play, and writing. The results suggest that ChatGPT can serve as an adaptable tool in ESP learning, although teachers must still guide students in verifying the accuracy of the information it provides.

Working more directly with reading, Kim and Jeong (2025) examined ESP learners' reading proficiency and perceptions when ChatGPT was incorporated into instruction. Their study is among the few to address ESP reading specifically rather than ESP language learning in general, and it underlines the value of examining how learners in particular disciplines engage with AI support while reading.

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Research Gap

Although this body of research demonstrates the potential of AI in EFL and ESP learning, most ESP studies have examined a single group of learners within one field of study. Comparative work remains scarce: little research has investigated how students from different disciplinary backgrounds use AI when reading specialised English texts.

The present study addresses this gap by comparing English-major and engineering students, in order to establish whether their differing linguistic and disciplinary foundations shape the reading difficulties they encounter and the ways in which they use AI when reading scientific and technological texts.

METHODOLOGY

Research Design

This study employed a cross-sectional comparative survey design to examine how English-major and engineering students use AI tools when reading scientific and technological English materials. A quantitative approach was adopted because the research questions concern the distribution of tool use, reported difficulties, and stated purposes across two defined groups, and the comparison of those distributions between the groups.

Participants

Participants were 88 undergraduate students at International Training Faculty, Thai Nguyen University of Technology, recruited by convenience sampling. Of these, 33 (37.5%) were students of English Language who had taken or were taking the module in English for Science and Technology, and 55 (62.5%) were students of engineering disciplines — including mechanical, electrical, electronics, and computer engineering — who regularly read technical materials in English. All four academic years were represented: 22 first-year, 22 second-year, 18 third-year, and 26 fourth-year students or above. Full participant characteristics are reported in Table 1.

Table 1. Participant Characteristics by Major

Characteristic	English majors n = 33	Engineering n = 55	Total N = 88	χ^2 (df), p
Academic year				6.81 (3), .078
First year	8 (24.2)	14 (25.5)	22 (25.0)	
Second year	10 (30.3)	12 (21.8)	22 (25.0)	
Third year	10 (30.3)	8 (14.5)	18 (20.5)	
Fourth year or above	5 (15.2)	21 (38.2)	26 (29.5)	
Self-rated reading proficiency				7.80 (3), .050
Low	5 (15.2)	4 (7.3)	9 (10.2)	
Moderate	20 (60.6)	47 (85.5)	67 (76.1)	
High	7 (21.2)	4 (7.3)	11 (12.5)	
Very high	1 (3.0)	0 (0.0)	1 (1.1)	
Frequency of reading S&T texts				3.69 (4), .450
Rarely	1 (3.0)	2 (3.6)	3 (3.4)	
Sometimes	13 (39.4)	25 (45.5)	38 (43.2)	
Often	12 (36.4)	24 (43.6)	36 (40.9)	
Very often	5 (15.2)	3 (5.5)	8 (9.1)	
Missing	2 (6.1)	1 (1.8)	3 (3.4)	

Note. Values are n (%) within each group. Total percentages are based on N = 88. Self-rated proficiency was measured on a 5-point scale; no participant selected Very low. Three participants did not answer the reading-

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frequency item; χ^2 tests exclude the Missing category.

Instrument

Data were collected through a self-developed questionnaire in English comprising seven sections: background information, reported reading difficulties, purposes of AI use, AI tool usage, perceived linguistic and content support and reading efficiency, perceived outcomes, and perceived challenges.

Three item formats were used. Background questions concerning major, academic year, self-rated reading proficiency, and reading frequency were single-choice. Questions 5, 6, and 7, which addressed tools used, difficulties encountered, and purposes of AI use, were multiple-response items. The remaining 25 items were measured on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) and were grouped into six sets: AI tool usage (AU, 4 items), linguistic support (LS, 4 items), content support (CS, 4 items), reading efficiency (RE, 4 items), perceived outcomes (PO, 4 items), and perceived challenges (CH, 5 items).

Internal consistency was acceptable for all six item sets: AU α = .847, LS α = .838, CS α = .838, RE α = .835, PO α = .853, and CH α = .868. Corrected item-total correlations exceeded .50 for every item, and the deletion of no single item would have raised the alpha of its set substantially.

Table 2. Questionnaire Structure and Internal Consistency

Scale / item set	No. of items	Cronbach's α
AI tool usage (AU)	4	.847
Linguistic support (LS)	4	.838
Content support (CS)	4	.838
Reading efficiency (RE)	4	.835
Perceived outcomes (PO)	4	.853
Perceived challenges (CH)	5	.868
Total	25	—

Note. Corrected item-total correlations exceeded .50 for every item, and deleting no single item would have raised the alpha of its scale substantially.

Data Collection and Ethical Considerations

The questionnaire was administered online. Participation was voluntary; students were informed of the purpose of the study before responding and were asked to answer on the basis of their own experience rather than in consultation with others. Responses were anonymised prior to analysis, and no information capable of identifying individual participants is reported. The data were used solely for academic research purposes.

Data Screening

Responses were screened before analysis. Three participants did not answer the reading-frequency item; analyses involving that variable are therefore based on n = 85. The number of valid cases is reported for each analysis rather than assumed constant across the dataset.

Screening also identified seven respondents who selected an identical value for all 25 Likert items, yielding zero within-person variance. These cases are referred to below as non-differentiating respondents. They were retained in the main analyses, but all group comparisons involving Questions 6 and 7 were repeated with these cases excluded as a robustness check; the outcome of that check is reported in Sections 4.3 and 4.4.

Data Analysis

Data were entered and analysed using IBM SPSS Statistics 27. Background characteristics were summarised using frequencies and percentages. Questions 5, 6, and 7 were analysed as multiple-response items, with percentages calculated on a respondent basis; these percentages consequently sum to more than 100%.

Between-group comparisons on the categorical variables were conducted using chi-square tests of independence without continuity correction, with Fisher's exact test applied where expected cell frequencies were small. Effect sizes are reported as phi coefficients and interpreted using the conventional benchmarks of .10, .30, and .50 for small, medium, and large effects respectively. The alpha level was set at .05 for all tests.

The six Likert item sets were summarised using means and standard deviations, and group means were compared using independent samples *t*-tests with Cohen's *d* as the effect size. A diagnostic analysis was additionally carried out on these data. Because the between-group difference proved to be of almost identical magnitude across all six item sets, including the Perceived Challenges set, each item score was centred on the respondent's own mean across the 25 Likert items and the group comparisons were repeated. The rationale for this procedure and its outcome are reported in Section 4.5 and discussed in Section 5.5.

RESULTS

Participant Characteristics

The comparability of the two groups was examined before the main analyses, since pre-existing differences in reading exposure, language proficiency, or academic seniority could confound the cross-disciplinary comparison. Table 1 presents the characteristics of the English-major (n = 33) and engineering (n = 55) participants.

Frequency of reading scientific and technological English texts did not differ significantly between the two groups, $\chi^2(4) = 3.69$, $p = .450$ (n = 85; three participants did not answer this item). In the English-major group, 39.4% (n = 13) reported reading such texts sometimes, 36.4% (n = 12) often, and 15.2% (n = 5) very often; the corresponding figures for the engineering group were 45.5% (n = 25), 43.6% (n = 24), and 5.5% (n = 3). Only 3.0% and 3.6% of the two groups respectively selected rarely.

Self-rated reading proficiency approached, but did not reach, conventional significance, $\chi^2(3) = 7.80$, $p = .050$. The majority of participants in both groups rated themselves at the moderate level, although this was more pronounced among engineering students (85.5%, n = 47) than among English majors (60.6%, n = 20). Ratings in the English-major group were more dispersed, with 15.2% (n = 5) at the low level and 21.2% (n = 7) at the high level, compared with 7.3% (n = 4) at each level among engineering students. One English major (3.0%) selected very high, and no participant selected very low.

The distribution of academic year did not differ significantly, $\chi^2(3) = 6.81$, $p = .078$. First-year students accounted for 24.2% (n = 8) of the English-major group and 25.5% (n = 14) of the engineering group; second-year students for 30.3% (n = 10) and 21.8% (n = 12); third-year students for 30.3% (n = 10) and 14.5% (n = 8); and fourth-year students or above for 15.2% (n = 5) and 38.2% (n = 21).

Taken together, these results indicate that the two groups were broadly comparable on the background variables most likely to confound the comparison, particularly exposure to scientific and technological texts. The borderline difference in self-rated proficiency, together with the greater dispersion of ratings within the English-major group, is acknowledged as a limitation and considered further in the discussion.

AI Tools Used

Patterns of AI tool selection were examined through a multiple-response item, with percentages calculated on a respondent basis. As shown in Table 3, tool use was highly consistent across the two groups.

Table 3. AI Tools Used by Major

AI tool	English majors n = 33	Engineering n = 55	Total N = 88	$\chi^2(1)$	p
ChatGPT	31 (93.9)	46 (83.6)	77 (87.5)	2.00	.157

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Gemini	10 (30.3)	27 (49.1)	37 (42.0)	2.99	.084
Claude	3 (9.1)	7 (12.7)	10 (11.4)	0.27	.603
Microsoft Copilot	3 (9.1)	2 (3.6)	5 (5.7)	1.15	.285
Grammarly	2 (6.1)	1 (1.8)	3 (3.4)	1.13	.288
DeepL	0 (0.0)	0 (0.0)	0 (0.0)	—	—
QuillBot	0 (0.0)	0 (0.0)	0 (0.0)	—	—

Note. Values are n (%) of respondents selecting each tool; participants could select more than one. Percentages are respondent-based and sum to more than 100%. χ^2 tests are computed on 2 × 2 tables without continuity correction; Fisher's exact test yielded the same pattern of results for all comparisons. No participant reported using DeepL or QuillBot.

ChatGPT was the dominant tool in both groups, with an overall adoption rate of 87.5% ($n = 77$). It was reported by 93.9% ($n = 31$) of English majors and 83.6% ($n = 46$) of engineering students, a difference that was not statistically significant, $\chi^2(1) = 2.00$, $p = .157$. Gemini was the second most widely used tool, reported by 42.0% ($n = 37$) overall; adoption was somewhat higher among engineering students (49.1%, $n = 27$) than among English majors (30.3%, $n = 10$), but this difference was likewise non-significant, $\chi^2(1) = 2.99$, $p = .084$.

The remaining tools were used far less frequently. Claude was reported by 11.4% ($n = 10$) of participants, $\chi^2(1) = 0.27$, $p = .603$; Microsoft Copilot by 5.7% ($n = 5$), $\chi^2(1) = 1.15$, $p = .285$; and Grammarly by 3.4% ($n = 3$), $\chi^2(1) = 1.13$, $p = .288$. Fisher's exact test yielded the same pattern of results for all comparisons.

Two features of these data are noteworthy. First, no tool differentiated the two groups: all comparisons yielded $p > .05$, indicating that disciplinary background was unrelated to which tools students selected. Second, and more strikingly, not a single participant in either group reported using a specialised machine translation tool such as DeepL or a paraphrasing tool such as QuillBot. General-purpose conversational systems built on large language models appear to have displaced dedicated translation and rewriting tools entirely within these students' academic reading practices.

Reported Reading Difficulties

Although the two groups used broadly similar tools, they reported markedly different profiles of reading difficulty (Table 4). Effect sizes are reported as phi coefficients and interpreted using the conventional benchmarks of .10, .30, and .50 for small, medium, and large effects respectively.

Table 4. Reported Difficulties in Reading Scientific and Technological English Texts by Major

Reported difficulty	English majors n = 33	Engineering n = 55	Total N = 88	$\chi^2(1)$	p	φ
Specialised vocabulary	20 (60.6)	6 (10.9)	26 (29.5)	24.47	< .001	.53
Technical concepts	11 (33.3)	41 (74.5)	52 (59.1)	14.49	< .001	.41
Complex English sentences	9 (27.3)	36 (65.5)	45 (51.1)	12.03	< .001	.37
Scientific background knowledge	1 (3.0)	24 (43.6)	25 (28.4)	16.72	< .001	.44
Logical structure	1 (3.0)	3 (5.5)	4 (4.5)	0.28	.597	.06

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Note. Values are n (%) of respondents selecting each difficulty; participants could select more than one. φ = phi coefficient (effect size for 2 × 2 tables). No participant selected the "Other" option. Results were substantively unchanged when the seven non-differentiating respondents were excluded (all $\varphi \geq .43$ for the four significant comparisons).

Specialised vocabulary was the most prominent barrier for English majors: 60.6% (n = 20) identified it as one of their main difficulties, compared with only 10.9% (n = 6) of engineering students, $\chi^2(1) = 24.47$, $p < .001$, $\varphi = .53$. The pattern reversed for technical concepts, which constituted the leading barrier among engineering students at 74.5% (n = 41), against 33.3% (n = 11) of English majors, $\chi^2(1) = 14.49$, $p < .001$, $\varphi = .41$.

Syntactic difficulty followed the same direction as conceptual difficulty. Complex English sentences were reported as a barrier by 65.5% (n = 36) of engineering students but by only 27.3% (n = 9) of English majors, $\chi^2(1) = 12.03$, $p < .001$, $\varphi = .37$. The largest asymmetry concerned scientific background knowledge, which was almost never a barrier for English majors (3.0%, n = 1) yet was reported by 43.6% (n = 24) of engineering students, $\chi^2(1) = 16.72$, $p < .001$, $\varphi = .44$.

Difficulty with the logical structure of texts was rare in both groups, at 3.0% (n = 1) and 5.5% (n = 3) respectively, and did not differ significantly, $\chi^2(1) = 0.28$, $p = .597$, $\varphi = .06$. No participant selected the other option.

These results describe two contrasting barrier profiles. Among English majors, difficulty was relatively localised and concentrated at the lexical level. Among engineering students, difficulty was broader in scope and operated simultaneously at three levels: the conceptual, the syntactic, and that of domain background knowledge. A robustness check excluding the seven non-differentiating respondents identified in Section 3.5 left this pattern unchanged, with $\varphi \geq .43$ for all four significant comparisons.

Purposes of AI Use

Table 5 presents the purposes for which participants reported using AI when reading scientific and technological texts. These purposes corresponded closely to the difficulties reported in the preceding section.

Table 5. Purposes of AI Use When Reading Scientific and Technological English Texts by Major

Purpose of AI use	English majors n = 33	Engineering n = 55	Total N = 88	χ²(1)	p	φ
Understanding specialised vocabulary	22 (66.7)	6 (10.9)	28 (31.8)	29.56	< .001	.58
Understanding technical concepts	9 (27.3)	46 (83.6)	55 (62.5)	27.96	< .001	.56
Translating difficult sentences	9 (27.3)	44 (80.0)	53 (60.2)	23.94	< .001	.52
Explaining grammar	6 (18.2)	20 (36.4)	26 (29.5)	3.28	.070	.19
Checking own understanding	1 (3.0)	4 (7.3)	5 (5.7)	0.69	.405	.09
Summarising texts	2 (6.1)	2 (3.6)	4 (4.5)	0.28	.597	.06
Scientific background knowledge	0 (0.0)	2 (3.6)	2 (2.3)	1.23	.268	.12
Understanding logical structure	0 (0.0)	0 (0.0)	0 (0.0)	—	—	—

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Note. Values are n (%) of respondents selecting each purpose; participants could select up to three. φ = phi coefficient. Results were substantively unchanged when the seven non-differentiating respondents were excluded (φ = .59, .64, and .56 for vocabulary, technical concepts, and translation, respectively).

Consistent with the lexical barrier they identified, 66.7% (n = 22) of English majors used AI to interpret specialised vocabulary, compared with 10.9% (n = 6) of engineering students, $\chi^2(1) = 29.56$, $p < .001$, φ = .58 — the largest effect observed in the study. Conversely, 83.6% (n = 46) of engineering students used AI to clarify technical concepts, against 27.3% (n = 9) of English majors, $\chi^2(1) = 27.96$, $p < .001$, φ = .56. A parallel gap appeared for the translation of difficult sentences, reported by 80.0% (n = 44) of engineering students and 27.3% (n = 9) of English majors, $\chi^2(1) = 23.94$, $p < .001$, φ = .52.

Grammar explanation was more common among engineering students (36.4%, n = 20) than among English majors (18.2%, n = 6), but the difference reached only borderline significance, $\chi^2(1) = 3.28$, $p = .070$, φ = .19. Using AI to obtain scientific background knowledge was rare overall (2.3%, n = 2), and both respondents belonged to the engineering group, $p = .268$.

A further finding concerns the purposes for which participants did not use AI. Checking one's own comprehension was reported by only 5.7% (n = 5) of the sample, $\chi^2(1) = 0.69$, $p = .405$; summarising texts by 4.5% (n = 4), $\chi^2(1) = 0.28$, $p = .597$; and analysing the logical structure of texts by no participant in either group. AI use was therefore concentrated almost exclusively on local decoding — resolving individual words, sentences, and concepts — rather than on higher-order comprehension strategies. Excluding the seven non-differentiating respondents again left the pattern unchanged, with φ = .59, .64, and .56 for vocabulary, technical concepts, and translation respectively.

Perceived Support and Challenges

Mean ratings on all six Likert item sets were above the scale midpoint in both groups, indicating broadly positive perceptions of AI support (see Appendix*,* Table 6). English majors returned higher means than engineering students on every item set, and all comparisons were significant at $p < .001$.

These differences are not interpreted as substantive. The gap between the two groups was almost constant across the six item sets, ranging only from +0.90 to +0.97, and it was of the same magnitude and direction on the Perceived Challenges scale (+0.97), where a reversed pattern would be expected had the groups genuinely differed in how helpful they found AI. Such uniformity is characteristic of a group difference in response style rather than in perception. Consistent with that interpretation, when each item score was centred on the participant's own mean across the 25 Likert items, no between-group difference remained significant (all $p \geq .45$).

The Likert data are therefore reported descriptively and are not used to support claims about differential perceived effectiveness between the two groups. The measurement implications of this finding are addressed in Section 5.5.

DISCUSSION

Overview

The findings indicate that AI tools have become a routine part of how students approach scientific and technological English texts. The more revealing question, however, is not whether students use AI but how they use it. Although English majors and engineering students selected largely the same tools, the two groups turned to those tools to solve different problems. English majors were constrained chiefly by specialised vocabulary, whereas engineering students faced a broader set of obstacles spanning technical concepts, complex sentence structures, and domain background knowledge.

This divergence is consistent with the linguistic character of scientific and technological texts, which differ from general English in information density, terminological load, nominalisation, and the frequency of passive constructions (Banks, 2005; Trișcă & Ionescu, 2017). Reading such texts requires readers not merely to decode individual lexical items but to integrate linguistic information with prior conceptual knowledge. The same tool may therefore serve markedly different functions depending on the reader's disciplinary foundation.

Similar Tools, Different Needs

A notable finding of this study is the absence of any statistically significant difference between the two groups in their choice of AI tools. ChatGPT was the most widely used tool overall (87.5%), reported by 93.9% of English majors and 83.6% of engineering students. Gemini ranked second at 42.0%, while Claude, Microsoft Copilot, and Grammarly were used at considerably lower rates. Notably, no participant in either group reported using a specialised machine translation tool such as DeepL or a paraphrasing tool such as QuillBot.

These results suggest that multifunctional conversational systems have become the default choice for processing academic texts, and that disciplinary background is not a primary determinant of tool selection (Baek et al., 2024; Onal et al., 2025). The convergence in tool choice, however, does not imply convergence in reading needs. On the contrary, the purposes for which the two groups used AI diverged sharply.

English majors used AI predominantly to explain specialised vocabulary: 66.7% of this group reported doing so, compared with only 10.9% of engineering students. The pattern reversed for conceptual support, with 83.6% of engineering students using AI to clarify technical concepts against 27.3% of English majors. A similar gap appeared for sentence-level translation, reported by 80.0% of engineering students and 27.3% of English majors. All three differences yielded large effect sizes.

Taken together, these results indicate that disciplinary background shapes how students use AI far more than which tool they select. Two students may open the same application and yet pose fundamentally different questions to it: an English major is likely to request the meaning of a technical term, whereas an engineering student is more likely to ask for a complex sentence to be unpacked or a specialised concept to be restated in simpler language.

AI Use Reflects Discipline-Specific Reading Barriers

The contrast in AI use can be traced directly to the reading difficulties the two groups reported. English majors struggled principally with specialised vocabulary. This is unsurprising: general proficiency in English does not entail familiarity with the terminological system of scientific and technical fields. Engineering students, by contrast, possessed stronger domain knowledge but had to carry out that processing in a second language, and their difficulties accordingly extended beyond vocabulary to concepts, syntax, and background knowledge.

The difference between the two groups should therefore not be reduced to a matter of English proficiency. Reading scientific and technological texts requires the simultaneous deployment of linguistic competence and specialised background knowledge (Carrell & Eisterhold, 1983; Nassaji, 2007). Without adequate domain knowledge, a reader may grasp the meaning of individual sentences yet fail to construct a coherent representation of the text's overall argument.

One finding warrants closeThao r attention. Engineering students reported substantially greater difficulty with technical concepts than English majors did (74.5% versus 33.3%). At first sight this appears paradoxical, since these are precisely the concepts in which engineering students are trained. The apparent contradiction dissolves once a distinction is drawn between possessing conceptual knowledge and being able to access that knowledge through an English-language text. A student may understand a concept thoroughly when it is presented in Vietnamese and still fail to recognise the same concept when it appears in dense academic English.

On this reading, the difficulties reported by engineering students do not necessarily indicate a deficit in specialised knowledge; they may instead reflect the challenge of mapping existing knowledge onto an unfamiliar linguistic form. This interpretation gives added significance to their heavy use of AI for concept explanation and sentence translation: in this context AI functions less as a translation utility than as a bridge between language and domain knowledge. The interpretation is, however, inferred from questionnaire responses rather than directly tested, and would require interview or think-aloud data to confirm.

AI Is Used for Local Decoding Rather Than Comprehension

A further finding is that AI use clustered almost entirely at the level of words, sentences, and concepts, while higher-order reading functions remained largely untouched. Only 5.7% of participants reported using AI to check their own understanding and 4.5% to summarise texts, and no participant in either group reported using it to analyse the logical structure of a text.

Students appear, in other words, to treat AI as a means of removing immediate obstacles encountered during reading. An unfamiliar word prompts a query; a difficult sentence prompts a request for translation or paraphrase; an unfamiliar concept prompts a request for clarification. Such use is plainly valuable, since it resolves local impasses and allows reading to continue.

Comprehending a scientific text, however, involves considerably more than defining words or rendering sentences. Readers must identify main ideas, recognise relations among concepts, follow the author's chain of reasoning, and monitor their own level of understanding (Klimova et al., 2025; Onal et al., 2025). Scientific texts are typically organised around a sustained argument, and understanding sentences in isolation does not guarantee that a reader has grasped the text's purpose or contribution.

The results therefore suggest that students are drawing on only a fraction of what these tools afford. Rather than asking what a word means or how a sentence should be translated, students could be guided towards questions such as what the main claim of a passage is, how its arguments relate to one another, or what questions would test whether the text has been understood. Used in this way, AI supports self-assessment and deeper engagement rather than substituting for the reader's own reasoning.

Interpreting the Perception Data

Both groups expressed positive views of AI support, with mean ratings above the scale midpoint on every Likert item set. The between-group difference, however, requires cautious interpretation. Although English majors returned higher means than engineering students on all six sets, the gap was almost constant, ranging only from 0.90 to 0.97 points, and it was of the same magnitude and direction on the Perceived Challenges scale, where a reversed pattern would be expected had the groups genuinely differed in how helpful they found AI.

When each item score was centred on the participant's own mean across the 25 Likert items, no between-group difference remained statistically significant. This pattern is characteristic of a group difference in response style rather than in perception. Acquiescent responding — the tendency to agree with items irrespective of their content — has been documented across a wide range of survey populations and is shaped by individual, situational, and cultural factors (Harzing, 2006; Lechner et al., 2019; Smith et al., 2016). The study therefore does not conclude that English majors perceive AI as more effective than engineering students do. The more defensible reading is that both groups hold broadly positive views, and that the initial score differences reflect divergent tendencies in the use of rating scales. This observation carries a methodological implication for subsequent research relying on self-reported Likert data in comparable populations.

Limitations

Several limitations qualify these findings. First, the sample comprised 88 students at a single institution, was recruited by convenience, and was unevenly distributed across the two groups (33 English majors and 55 engineering students); the results are therefore not generalisable beyond this setting. Second, all data were self-reported, and no independent measure of reading performance was obtained, so the study captures perceived rather than demonstrated support. Third, English proficiency was assessed only through self-rating; the borderline difference between groups on this variable ($p = .050$), together with the greater dispersion of ratings among English majors, cannot be fully ruled out as a contributing factor.

Fourth, the Likert scales contained no reverse-worded items, and the analysis reported in Section 5.5 indicates that responses were affected by differential response style; the perception data are consequently reported descriptively only. Fifth, the cross-sectional design permits no causal inference about the effects of AI use on reading development. Finally, Question 6 instructed respondents to select a single option but was in practice answered as a multiple-response item; it was analysed accordingly, and this discrepancy should be corrected in future administrations of the instrument.

Implications for AI Use in ESP Reading

These findings suggest that integrating AI into the reading of scientific and technological English should not follow a uniform model. For English majors, AI is most usefully directed towards explaining terminology, building specialised vocabulary systematically, and developing background knowledge in technical fields. For engineering students, it is most usefully directed towards bridging the gap between existing technical expertise and its English-language expression, particularly through work on complex sentence structures and the restatement of concepts.

More importantly, both groups would benefit from guidance in moving beyond translation and definition towards uses that support deep comprehension: summarising, identifying main ideas, analysing argument structure, generating comprehension questions, and assessing their own understanding. This is consistent with the view that the pedagogical value of AI depends less on the capability of the technology than on the learner's purpose and manner of use (Lim & Teh, 2026).

Overall, the principal distinction between English majors and engineering students lies not in the tools they use but in the difficulties they need those tools to address. English majors require support at the level of specialised terminology; engineering students require it at the intersection of language, syntax, and technical knowledge. The integration of AI into scientific and technological English instruction should accordingly be tailored to the needs, disciplinary background, and reading goals of each group, while encouraging students to treat AI as a support for critical engagement rather than a substitute for their own reading and reasoning.

CONCLUSION

This study examined how English-major and engineering students at a Vietnamese university use AI tools when reading scientific and technological English materials. AI has become a routine part of academic reading for both groups, yet the two groups drew on it in markedly different ways, shaped by their disciplinary backgrounds.

Tool selection was almost identical. ChatGPT dominated in both groups, and no comparison of tool use reached statistical significance. What differed was the kind of reading problem each group needed to solve. For English majors, specialised vocabulary was the principal barrier, although conceptual and syntactic difficulties were also reported by a substantial minority. For engineering students, difficulty lay less in terminology than in technical concepts, complex sentence structures, and the scientific background knowledge that such texts assume.

These contrasting profiles can be traced to the resources each group brings to the task. English majors command stronger general language proficiency but are less familiar with the terminological systems of technical fields. Engineering students possess the relevant domain knowledge but must access it through academic English, whose information density and syntactic complexity present obstacles of their own.

The same contrast appeared in how the two groups used AI. English majors turned to AI chiefly to interpret specialised vocabulary, whereas engineering students used it to clarify technical concepts and to translate difficult sentences; all three differences yielded large effect sizes. In both groups, purposes requiring higher-order processing — summarising, checking one's own comprehension, and analysing the logical structure of a text — were rare. AI use was therefore concentrated at the level of local decoding rather than sustained analysis.

These findings carry implications for the teaching of AI-assisted ESP reading. Students should be encouraged to treat AI as more than a device for looking up words and translating sentences. They can be guided to request explanations of the concepts underlying a passage, to verify their own understanding against the text, to compare explanations across sources, and to evaluate the accuracy of what AI provides. Such practices matter particularly in scientific and technological reading, where an inaccurate AI explanation may distort a student's understanding of specialised content.

Guidance should also be differentiated. For English majors, the priority is the systematic development of specialised vocabulary and technical background knowledge; for engineering students, it is the capacity to process dense academic English and to recognise familiar concepts in unfamiliar linguistic form.

Future research could extend this comparison to a wider range of institutions and disciplines, incorporate objective measures of reading performance alongside self-report, and test whether explicit training in AI use improves reading comprehension, critical evaluation, and learner autonomy.

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Table 6 Appendix: Group Means on the Likert Item Sets

Item set	English majors M (SD)	Engineering M (SD)	Mean difference	Cohen's d
AI tool usage (4 items)	4.48 (0.45)	3.55 (0.45)	+0.93	2.08
Linguistic support (4 items)	4.48 (0.38)	3.55 (0.41)	+0.93	2.31
Content support (4 items)	4.44 (0.31)	3.54 (0.46)	+0.90	2.19
Reading efficiency (4 items)	4.47 (0.27)	3.52 (0.38)	+0.95	2.76
Perceived outcomes (4 items)	4.45 (0.43)	3.50 (0.44)	+0.95	2.14
Perceived challenges (5 items)	4.44 (0.38)	3.47 (0.44)	+0.97	2.31

Note. Values are group means (standard deviations) on 5-point scales. All between-group differences were significant at $p < .001$. These figures are reported for transparency but are not interpreted as substantive differences: the near-identical magnitude of the difference across all six item sets — including perceived challenges, where a reversed pattern would be expected — indicates a group difference in response style rather than in perception. When responses were centred on each participant's own mean across all 25 items, no between-group difference remained (all $p \geq .45$). See the Methods section for further discussion.