A Human–AI Collaborative Read–Think–Write Framework for ESP-Oriented College English Education: Development and Pedagogical Applications

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Abstract: Generative artificial intelligence (GenAI) offers adaptive materials and rapid feedback for language education, but its classroom use often remains fragmented and weakly connected to disciplinary learning and student reasoning. This framework-development study proposes a Human–AI Collaborative Read–Think–Write Framework for ESP-oriented College English education in large science and engineering classes at a local application-oriented university in Guangxi, China. Developed through practice-informed problem identification, contextual needs analysis, theoretical synthesis, interdisciplinary co-design, and three rounds of refinement, the framework integrates Reading-to-Write Pedagogy with Human–AI Collaboration. It comprises one core—human–AI collaborative personalized learning; two drivers—content customization and feedback immediacy; and three loops—AI-assisted reading, AI-guided thinking, and AI-supported writing. A process-evidence assessment chain connects the initial draft, AI interaction records, revised draft, and reflective statement. Its pedagogical application is illustrated through an ESP unit on autonomous vehicles and road safety. the framework offers a teacher-governed, tool-neutral approach that positions GenAI as a scaffold rather than an author. Its effectiveness requires future external review, classroom piloting, and mixed-method validation.

Keywords: Generative Artificial Intelligence; Human–Ai Collaboration; Reading-To-Write; English For Specific Purposes; College English; Framework Development

1. Introduction

Generative artificial intelligence (GenAI), particularly large language model-based conversational systems, has prompted higher education to reconsider teaching, learning, and assessment. In language education, GenAI can adapt texts, explain terminology, generate questions, support brainstorming, and provide rapid feedback. These functions are valuable in College English courses with large and heterogeneous classes. However, GenAI may also produce inaccurate information, fabricated references, generic arguments, and polished language that masks limited student understanding. the key issue is therefore how AI can be integrated in ways that support, rather than replace, reading, reasoning, and writing (Kasneci et al., 2023; Kohnke et al., 2023; Tlili et al., 2023).

This issue is particularly relevant in Chinese higher education. the national Action Plan for “Artificial Intelligence+Education” promotes deeper AI integration, human–machine collaboration, teacher development, and AI-related competencies (Ministry of Education of the People’s Republic of China et al., 2026). Nevertheless, policy direction does not automatically translate into workable classroom pedagogy. Local application-oriented universities must develop feasible practices that consider student proficiency, disciplinary diversity, class size, teacher workload, and academic integrity.

The present framework was developed for College English I–IV courses serving science and engineering undergraduates at a local public university in Guangxi, China. Although each administrative class contains approximately 37 students, College English is commonly delivered to combined classes of more than 90 students. Experienced instructors have observed persistent difficulties in reading comprehension, written expression, and the transfer of ideas from reading to writing. These difficulties are intensified by three structural problems: reading and writing are often taught separately, general English materials may lack disciplinary relevance, and large classes limit individualized and iterative feedback.

GenAI may help address these problems, but unstructured use creates further risks. Students may rely on AI for translation, correction, or direct text generation, while teachers may reduce it to an automated marking tool. AI-generated disciplinary content may also be inaccurate or misaligned with course objectives. Although previous research has identified both the benefits and risks of AI-supported language learning, teachers still need operational models that coordinate source reading, critical processing, writing, revision, and transparent AI use (Mahapatra, 2024; Nguyen et al., 2024).

This article therefore develops a Human–AI Collaborative Read–Think–Write Framework for ESP-oriented College English education. It addresses the following question: How can GenAI support disciplinary reading-to-writing development while preserving student agency, teacher oversight, and assessable evidence of learning? the study makes three contributions. First, it integrates Reading-to-Write Pedagogy with Human–AI Collaboration to define both the instructional sequence and the distribution of responsibility. Second, it proposes an operational structure of one core, two drivers, and three loops, supported by responsible-use safeguards and a process-evidence assessment chain. Third, it illustrates pedagogical application through disciplinary theme mapping and an ESP unit on autonomous vehicles and road safety. As a framework-development study, it does not report student outcomes but offers a theoretically grounded design for future validation.

2. Conceptual Foundations

2.1 Reading-to-Write Pedagogy

Reading-to-Write Pedagogy views reading and writing as connected meaning-making processes. In academic and professional communication, writers must interpret sources, compare claims, select evidence, and reorganize information for a new rhetorical purpose. Integrated tasks therefore require comprehension, source use, and composition to operate together (Cumming et al., 2005; Grabe & Zhang, 2013).

Research shows that second-language writers differ in how they select, paraphrase, synthesize, and connect source information to their own arguments (Plakans, 2009; Plakans & Gebril, 2012). Successful performance depends not only on language accuracy but also on planning, evidence evaluation, and rhetorical organization. Without explicit guidance, less proficient students may copy source language, summarize without developing a position, or use evidence mechanically (Weigle & Parker, 2012).

The proposed framework therefore makes “think” an explicit bridge between reading and writing. Students evaluate claims, examine evidence, identify perspectives, and develop a provisional position before drafting. Notes, responses, outlines, and argument maps make this reasoning process visible and assessable while reducing the risk of moving directly from AI-generated reading materials to AI-polished writing.

2.2 Human–AI Collaboration

Human–AI Collaboration treats AI as a supporting participant rather than a substitute for teachers or learners. Effective educational collaboration combines human judgment, disciplinary knowledge, values, and responsibility with AI capabilities such as adaptation, rapid generation, and scalable feedback (Molenaar, 2022; Ouyang & Jiao, 2021).

In writing instruction, GenAI can assist with idea development, language reformulation, and formative feedback, but outcomes depend on how users regulate and evaluate its contributions (Nguyen et al., 2024). Unrestricted use may also create risks involving inaccurate information, bias, privacy, dependence, and academic integrity (Kasneci et al., 2023; Kohnke et al., 2023; UNESCO, 2023).

The framework therefore follows five principles: complementarity, human agency, teacher governance, transparency, and traceability. Teachers define objectives, approve content, and conduct assessment; AI provides adaptable scaffolding and feedback; students remain responsible for interpretation, decision-making, and authorship. Meaningful AI assistance must be disclosed, and interaction records should be retained as evidence of the learning process.

2.3 Integrating the Two Foundations

The two foundations serve complementary purposes. Reading-to-Write Pedagogy defines the learning sequence, while Human–AI

Collaboration allocates roles and responsibilities. Their integration produces four design principles: AI support should operate throughout the literacy process; reading should lead to writing through explicit critical thinking; AI should reduce access and feedback barriers without reducing cognitive effort; and assessment should consider both the final text and the process that produced it. These principles guide the framework developed in the following section.

3. Framework Development Methodology

This study adopted a conceptual, design-oriented framework-development approach. No students were recruited, and no surveys or learning outcomes were collected because the intended 2026 and 2027 cohorts had not yet entered the university. the study was therefore prospective, aiming to establish a coherent pedagogical architecture, implementation logic, and validation agenda for future classroom research. Consistent with educational design research, it focused on identifying a practical problem, developing a theoretically informed solution, and refining that solution before empirical testing (McKenney & Reeves, 2019).

The framework was designed for College English I–IV at a local application-oriented public university in Guangxi, China. Its intended users are undergraduates in 18 science- and engineering-related programs across six disciplinary areas: mathematics and computing, physics and information engineering, biological and food engineering, automotive engineering, chemistry and materials, and advanced manufacturing. College English classes commonly exceed 90 students, creating a need for scalable differentiation and feedback. This contextual description defines the design constraints rather than providing evidence of effectiveness.

An interdisciplinary team of more than ten faculty members developed the framework. the team included senior College English instructors with more than 15 years of teaching experience and faculty members specializing in artificial intelligence and educational technology. Because the developers also conducted the review process, their deliberations are described as internal interdisciplinary consultation rather than independent external validation.

Framework development proceeded through five stages. First, problem identification synthesized recurring challenges reported by frontline teachers, including reading–writing separation, limited disciplinary relevance, delayed feedback, superficial AI use, and unclear teacher–AI–student roles. Second, a practice-informed contextual needs analysis interpreted these issues through classroom observation, teacher feedback, disciplinary demands, and College English teaching conditions. No formal student survey or systematic textbook analysis was conducted.

Third, theoretical synthesis used Reading-to-Write Pedagogy to organize the learning sequence and Human–AI Collaboration to allocate agency, support, and accountability. ESP principles also informed the emphasis on disciplinary relevance and adaptable materials (Anthony, 2018; Basturkmen, 2010). Fourth, initial construction translated these principles into participant roles, a read–think–write process, prompt-library functions, and assessment evidence. Fifth, three rounds of internal refinement addressed conceptual clarity, classroom feasibility, role boundaries, and memorability. the final structure was summarized as “One Core, Two Drivers, and Three Loops. ”

Because no human-participant data were collected, the study makes no claims of effectiveness or validated impact. Future implementation should obtain appropriate ethical approval and establish informed-consent, privacy, and data-governance procedures before collecting student work, interaction records, or performance data.

4. the Human–AI Collaborative Read–Think–Write Framework

4.1 Overview

The framework consists of one core, two drivers, and three connected instructional loops. the core is human–AI collaborative personalized learning. the two drivers are content customization and feedback immediacy. the three loops are AI-assisted reading, AI-guided thinking, and AI-supported writing. Figure 1 represents the structure as a governed cycle rather than a linear automation pipeline. Teachers establish objectives, authorize resources, and make assessment decisions; students read, reason, draft, revise, and reflect; AI supplies bounded support at designated points. Each writing cycle can feed forward into subsequent reading because revision needs reveal vocabulary, knowledge, or reasoning gaps that require new input.

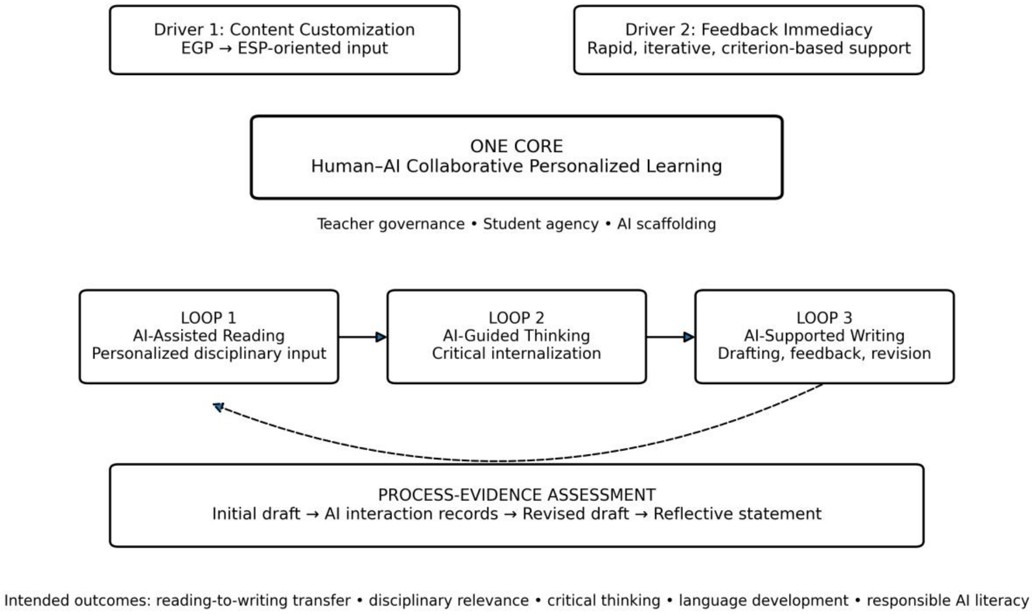

Figure 1. Structure and Governance of the Human–AI Collaborative Read–Think–Write Framework.

4.2 One Core: Human–AI Collaborative Personalized Learning

Personalization in the framework does not mean allowing an AI system to decide the curriculum independently. It means adjusting support within teacher-defined objectives. the teacher acts as curriculum designer, prompt designer, disciplinary-language mediator, thinking facilitator, and final evaluator. the AI system acts as an adaptive resource generator, conversational scaffold, and rapid feedback provider. the student remains the reader, reasoner, author, verifier, reviser, and reflective decision-maker. This triadic structure is intended to prevent two common distortions: teacher withdrawal through automation and student withdrawal through text generation.

Role boundaries are consequential. Teachers select or approve content, specify language level and rhetorical purpose, identify non-negotiable learning outcomes, review potentially inaccurate disciplinary information, and determine what forms of AI assistance are permitted. AI may adapt a text, explain terms, ask questions, compare outlines, identify unclear reasoning, or classify language problems, but it does not assign final grades or determine whether a student has met the learning outcome. Students must evaluate AI outputs, retain or reject suggestions with reasons, and accept responsibility for the final submission. Personalization is therefore achieved through adjustable scaffolding under stable human governance.

Table 1. Role Allocation in the Teacher–AI–Student Triad.

Actor	Primary agency	Authorized functions	Non-delegable responsibility
Teacher	Pedagogical governance	Set objectives; design prompts; approve sources; diagnose learning; provide targeted feedback	Final content approval and assessment
AI system	Bounded computational support	Adapt texts; explain terms; ask questions; identify issues; provide rapid criterion-based feedback	No autonomous grading, authorship, or factual authority
Student	Learning and authorship	Read; reason; draft; verify; select feedback; revise; reflect	Responsibility for claims, decisions, and final submission

4.3 Two Drivers

The first driver, content customization, addresses the mismatch between standardized general English materials and heterogeneous disciplinary interests. A program-specific prompt library can help teachers transform an existing topic into an ESP-oriented reading package at an appropriate language level. A prompt may specify the target program, communicative purpose, length, key terminology, rhetorical pattern, and types of comprehension or critical-thinking questions. For example, a general unit on technology may be adapted for intelligent vehicle engineering through a text on sensor fusion and road safety, or for food science through a text on AI-supported contamination monitoring. Customization is not unconstrained generation: teachers should verify technical accuracy, remove fabricated data or citations, check language load, and ensure that the material serves the course objective rather than becoming a miniature specialist lecture.

The second driver, feedback immediacy, addresses the practical limits of large-class writing instruction. In a class of more than 90 students, teachers cannot provide multiple rounds of detailed sentence-level and discourse-level feedback to every learner within a short period. AI can supply rapid first-line feedback organized by teacher-defined criteria. However, speed is not equivalent to validity. the framework therefore uses staged feedback. AI first identifies issues and asks revision questions; students decide how to respond; peers or the teacher then focus on higher-value concerns such as evidence, disciplinary appropriateness, and argument quality. Teacher attention is redirected rather than removed.

4.4 Three Instructional Loops

AI-assisted reading is the personalized-input loop. the teacher begins with a verified source, an instructor-written text, or an approved content brief. AI may then adjust lexical difficulty, generate a glossary, explain background concepts, segment the text, highlight rhetorical moves, or produce tiered comprehension questions. Students should encounter the substantive text before seeing an AI-generated summary so that summarization does not replace reading. Typical student products include annotated passages, terminology logs, claim–evidence tables, and short source summaries. At this stage, AI reduces access barriers, while the student remains responsible for comprehension and source checking.

AI-guided thinking is the critical-internalization loop and the distinctive bridge within the framework. AI is prompted to question rather than answer for the student. It may ask learners to compare claims, identify assumptions, test the quality of evidence, distinguish correlation from causation, consider stakeholder perspectives, or explain a counterargument. Students record their own position before requesting model suggestions, then compare the model's response with their reasoning. Required intermediate products may include an argument map, a stakeholder matrix, a claim–evidence–reasoning chart, or a structured outline. Teachers can inspect these products to determine whether the final essay is grounded in an observable reasoning process.

AI-supported writing is the interactive-output loop. Students first produce an initial draft from their reading notes and thinking products. This requirement protects authorship and gives the teacher a baseline sample of the student's independent performance. AI feedback is then requested through bounded prompts such as "identify two places where the evidence does not fully support the claim" or "explain the coherence problem without rewriting the paragraph. " Direct generation of a complete replacement essay is not permitted. Students revise through one or more cycles, maintain a brief decision log, and submit the final text with an AI-use statement. the aim is not simply a more fluent product but a more deliberate revision process.

The loops are recursive. A writing problem may reveal weak comprehension, prompting renewed reading. A thinking question may expose missing evidence, prompting source expansion. AI feedback may identify a disciplinary term used inaccurately, prompting consultation with teacher-approved resources. Recursion makes the framework a learning cycle rather than a one-way content-production workflow.

4.5 Assessment and Responsible-Use Guardrails

Assessment follows a process-evidence chain: initial draft → AI interaction records → revised draft → reflective statement. the initial draft indicates what the student can produce before AI-mediated revision. Interaction records show the prompts used, the scope of support, and the student's selection of feedback. the revised draft demonstrates change, while the reflective statement explains major decisions, rejected suggestions, fact-checking actions, and remaining weaknesses. This chain does not perfectly separate human and machine contributions, but it makes the collaboration more transparent and assessable than a final product alone.

A proposed analytic rubric assigns 20% to reading comprehension and source use, 15% to disciplinary relevance, 20% to critical thinking and argumentation, 15% to organization and coherence, 20% to language quality, and 10% to revision quality and transparent AI use. the rubric is conceptual and requires later validation.

Responsible-use guardrails include the following: students must not request or submit a fully AI-generated essay; factual claims and references must be checked against teacher-approved sources; sensitive personal data must not be entered into public systems; meaningful AI assistance must be disclosed; and final grading remains a teacher responsibility. Institutions should also provide equivalent non-AI alternatives when access is unequal or a student has a legitimate reason not to use a particular system.

Table 2. Proposed Analytic Assessment Dimensions.

Assessment dimension	Weight	Indicative evidence
Reading comprehension and source use	20%	Accurate interpretation, selection, paraphrase, and integration of source information
Disciplinary relevance	15%	Appropriate concepts, terminology, audience, and professional context
Critical thinking and argumentation	20%	Claims, evidence, warrants, counterargument, and justified position
Organization and coherence	15%	Purposeful structure, progression, cohesion, and paragraph unity
Language quality	20%	Accuracy, range, precision, register, and readability
Revision and transparent AI use	10%	Consequential revision, disclosure, verification, and reflection

5. Pedagogical Applications

5.1 Cross-Disciplinary Applicability

The framework is tool-neutral and can be adapted across disciplinary clusters by changing the content brief, terminology, source set, thinking problems, and communicative task while preserving the same Read–Think–Write logic. Possible themes include responsible GenAI in software development, communication technologies and public safety, AI in food-quality monitoring, autonomous vehicles and road safety, sustainable materials, and human–robot collaboration in smart manufacturing. Such applications do not convert College English into a specialist content course. Rather, they use disciplinary relevance to create meaningful reasons for reading, discussion, evidence use, and written communication.

Table 3. Illustrative Pedagogical Applications Across Disciplinary Clusters.

Disciplinary cluster	Illustrative ESP theme	Possible writing purpose
Mathematics and computing	Responsible GenAI in software development	Policy recommendation
Physics and information engineering	Communication technologies and public safety	Problem–solution report
Biological and food engineering	AI in food-quality monitoring	Evidence-based explanation
Automotive engineering	Autonomous vehicles and road safety	Argumentative evaluation
Chemistry and materials	Sustainable materials and lifecycle trade-offs	Comparative analysis
Advanced manufacturing	Human–robot collaboration in smart factories	Risk–benefit assessment

5.2 Illustrative Unit: Autonomous Vehicles and Road Safety

This illustrative unit is designed for students in intelligent vehicle engineering and related automotive programs and may be used in College English III. It requires approximately three to four class hours plus independent drafting. the objectives are to understand an adapted ESP text, use key automotive and safety terminology, evaluate competing claims, develop an evidence-based argument, revise writing through bounded AI feedback, and disclose AI use responsibly.

In the AI-assisted reading loop, the teacher provides two verified texts: a technical overview of autonomous driving systems and a discussion of safety, liability, human factors, and deployment conditions. Key terms may include sensor fusion, object detection, operational design domain, fallback system, disengagement, human–machine handover, and vulnerable road users. AI may provide glosses, explain text structure, and generate tiered questions, while teachers verify technical, statistical, and legal information. Students complete a claim–evidence table and identify expressions of certainty, limitation, and recommendation.

In the AI-guided thinking loop, students consider the question: Should fully autonomous vehicles be widely introduced before their safety clearly exceeds that of human-driven vehicles? Before consulting AI, they record an initial position and supporting reasons. A teacher-designed prompt then directs AI to question assumptions, request evidence, introduce stakeholder perspectives, and identify missing conditions without generating an essay. Students examine the interests of passengers, pedestrians, manufacturers, regulators, insurers, professional drivers, and emergency services. They then construct an argument map containing a thesis, supporting claims, a counterclaim, a rebuttal, and relevant evidence.

The writing task asks students to produce a 700–900-word argumentative essay evaluating whether autonomous vehicles can improve road safety and identifying the technical, regulatory, and ethical conditions required for responsible deployment. During the AI-supported writing loop, students request criterion-based feedback rather than replacement text. AI may identify unsupported claims, unclear rebuttals, inaccurate terminology, or coherence problems. Students evaluate the feedback, revise the draft, and record three important revision decisions.

The final submission includes the initial draft, selected AI interaction records, the revised essay, and a 150-word reflection. In classes exceeding 90 students, AI can provide first-line feedback outside class, while classroom time is used for teacher modelling, peer comparison, discussion of questionable AI suggestions, and targeted conferencing. the teacher may also use sampled interaction records to design mini-lessons on evidence, hedging, source integration, or technical vocabulary.

The unit can be differentiated through shorter texts, bilingual terminology, paragraph frames, or progressively sequenced questions for less proficient students. More advanced students may compare conflicting sources or write for a professional audience. In all versions, students remain the authors, while teachers retain pedagogical and evaluative authority.

6. Discussion and Pedagogical Implications

The framework contributes to reading-to-write pedagogy by making the cognitive transition from reading to writing explicit. Through AI-guided thinking, students evaluate evidence, form positions, and organize arguments before drafting, thereby connecting comprehension, source use, and composition (Grabe & Zhang, 2013; Plakans & Gebril, 2012).

It also provides a bounded model of Human–AI Collaboration. AI may adapt texts, generate questions, and provide criterion-based feedback, while teachers retain control over objectives, content quality, and assessment. Students remain responsible for interpretation, argumentation, and authorship. This division of responsibility is important because AI-supported writing depends on interaction design rather than tool availability alone (Nguyen et al., 2024).

The framework further offers a practical route from general English to ESP-oriented instruction. GenAI can reduce the time required to adapt disciplinary materials, but teacher verification and professional judgement remain essential (Anthony, 2018; Basturkmen, 2010). Its tool-neutral structure also allows institutions to select systems according to local infrastructure, proficiency levels, curriculum time, and assessment policies.

The framework has not yet been externally validated or implemented with the intended cohorts. Its needs analysis relied mainly on teacher observations, and variation among GenAI systems may affect implementation. Future research should therefore include external review, classroom pilots, mixed-method evaluation, and longitudinal investigation of whether AI-supported improvements lead to durable and independent learning.

7. Conclusion

This article has developed a Human–AI Collaborative Read–Think–Write Framework for ESP-oriented College English education in large, interdisciplinary science and engineering classes. Reading-to-Write Pedagogy provides the integrated literacy sequence, while Human–AI Collaboration establishes role boundaries, human oversight, and student responsibility. the framework organizes practice around one core of collaborative personalized learning, two drivers of content customization and feedback immediacy, and three recursive loops of AI-assisted reading, AI-guided thinking, and AI-supported writing. Its process-evidence assessment chain is intended to make AI participation visible without treating technological traces as a perfect measure of authorship. the autonomous-vehicles unit illustrates how the framework can convert disciplinary relevance into purposeful reading, critical analysis, and evidence-based writing. the framework's value currently lies in its conceptual coherence and operational specificity, not in demonstrated effectiveness. Its next stage is rigorous external review and classroom validation.

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