Generative AI as a Cognitive Co-Participant: Disciplinary Modulation of EFL Academic Reading Load and Motivation

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Abstract

As generative AI rapidly enters higher education, its cognitive, motivational, and social impacts across disciplines remain underexplored. This qualitative study examines disciplinary epistemologies and digital literacy on AI-assisted academic reading among EFL Chinese students. Guided by Cognitive Load Theory and Self-Determination Theory, participants were 46 university students across Biglan's disciplinary dimensions. We analyzed 46 questionnaires and 32 interviews. Students in soft and applied fields more often report AI reducing intrinsic load, supporting deeper semantic elaboration. In pure and hard fields, students tend to use AI as an interactive tool for questioning, but multi-contextual examples are more likely to introduce extraneous load. By contrast, terminology glossing and decomposition of complex sentences are more often applied in soft and applied fields. Excessive reliance is associated with cognitive offloading and an illusory sense of mastery, shaped by digital literacy and metacognitive awareness. Socially, AI sometimes displaces routine exchanges, but when integrated into group contexts, it facilitates collaboration. The study elaborates applications of CLT and SDT by showing how disciplinary and individual factors shape AI's cognitive and motivational roles. Practically, it proposes discipline-sensitive design principles and metacognitive prompts, pointing to deployable interventions. Ethical approval and consent were obtained.

Introduction

Academic English reading is essential for EFL learners (Nergis 2013) but is challenged by barriers, such as vocabulary gaps, complex syntax, and inference demands (Gao 2020; Shepard and Rose 2023). These linguistic difficulties create cognitive and motivational obstacles, limiting engagement with academic texts. AI-enabled support has shown promise in lowering these barriers and fostering deeper cognitive involvement (Fu and Hiniker 2025).

Recent advances in generative AI (Gen AI) help reduce extraneous cognitive load through functions such as text simplification (Higasa et al. 2023; Guidroz et al. 2025). These affordances enhance surface comprehension and free cognitive resources for deeper processing. However, its impact varies across disciplines. To explain, students in hard disciplines tend to view AI as a functional assistant that reduces cognitive burden, supporting efficiency and precision in learning tasks (Wang et al. 2024; Guidroz et al. 2025), while soft discipline students rely more on semantic and multi-perspective integration, where AI support is weaker (Shi-xu 2024; Fan et al. 2024). Given these differences, each discipline's cognitive structure and epistemic demands need to be considered in the discussion of effective AI integration.

Building on these insights, this study uniquely integrates Cognitive Load Theory (CLT) and Self-Determination Theory (SDT) to examine how disciplinary paradigms modulate AI's effects on cognitive load regulation and motivation among Hong Kong EFL students. We examine the cognitive-motivational mechanisms of AI-assisted reading, and transfer these findings into concrete guidelines for designing discipline-sensitive AI reading assistants, curriculum scaffolds, and adaptive instructional support systems to bridge empirical research and deployable educational innovations. This research addresses three key questions:

RQ1: How do disciplinary paradigms shape the boundary between beneficial and excessive cognitive automation in AI-assisted EFL reading?

RQ2: What mechanisms underlie the illusion of competence, and how can strategy-transfer approaches mitigate pseudo-competence risks?

RQ3: How does AI-mediated reading influence learners' autonomy and relatedness, and how can instructional design balance efficiency with interactive depth?

Literature Review

Though the ability to understand academic texts is one of the most important skills for EFL students to possess (Nergis 2013), research on undergraduate reading is not prevalent, especially regarding their experiences and perceptions of academic reading (Maguire, Reynolds, and Delahunt 2020). To bridge this gap, the present study will delve into university students' reading experiences and perceptions.

Cognitive Load in EFL Academic Reading

Academic reading is challenged by vocabulary gaps, complex syntax, and inference demands (Gao 2020; Shepard and Rose 2023). These barriers create cognitive and motivational obstacles to engagement. AI-enabled support helps lower these barriers and fosters deeper cognitive involvement (Fu and Hiniker 2025).

Academic reading imposes a multi-layered cognitive burden on EFL learners, especially with dense and abstract texts involving vocabulary, discourse, and reasoning (Day and Bamford 1998). Intrinsic load stems from task complexity and prior knowledge, while extraneous load arises from instructional design (Sweller 2010). Regional differences appear. Mainland Chinese students face diverse linguistic and non-linguistic barriers, while in Hong Kong, limited vocabulary knowledge is primary (Gao 2020; Shepard and Rose 2023).

Most studies treat reading barriers holistically; few explore linguistic versus non-linguistic aspects (Gao 2020). This study adopts Gao's classification and examines AI's regulatory impact on EFL students' language barriers.

Disciplinary Paradigms and Cognitive Strategies

Biglan pioneeringly created lasting framework for higher education, based on the classification of academic disciplines (Bray, 2008). This framework has been applied by various scholars until now (Qu and Wang, 2025; Neumann, Parry and Becher, 2002). He divided disciplines into two main categories, namely pure VS applied and hard VS pure. Disciplinary paradigms differ between fields, producing heterogeneous strategic demands. Soft fields like education lack unified paradigms and emphasize discourse negotiation; hard fields like engineering stress standardized, structured expression (Biglan 1973; Schommer-Aikins, Duell and Barker 2003). These differences require distinct cognitive strategies. However, teaching often overlooks interdisciplinary strategy transfer, affecting knowledge integration due to intrinsic, extrinsic, and relational cognitive loads (Morales 2025).

Prior research mainly focuses on AI use within single disciplines (Menekse 2023; Ke 2023). Sun et al. (2025) analyzed AI use across five Mainland China fields, revealing distinct discipline-specific patterns. Building on this and considering Hong Kong's program structures, this study investigates AI adoption and cognitive load relief within its disciplinary contexts.

AI: a Dual-Support Tool for Load and Motivation

Generative AI tools support EFL learners by simplifying complex texts and enhancing reading effectiveness (Zheng and Fan 2024; Fu and Hiniker 2025). From a Cognitive Load Theory perspective, AI reduces extraneous load, improving comprehension and efficiency (Higasa et al. 2023). However, processing unfamiliar content may increase working memory demands (Sweller 1988).

Risks include overdependence on AI, which may reduce learners' initiative and metacognitive monitoring (Fan et al. 2024; Gkintoni et al. 2025). Learners' cultural capital influences whether AI is treated as a thinking partner or an authoritative source, affecting self-regulated learning.
Self-Determination Theory highlights that AI can enhance competence but may reduce autonomy if user choices are restricted, potentially causing a dependency cycle (Ryan and Deci 2000; Shen and Cui 2024; Faas et al. 2024). Thus, AI plays dual roles, facilitating access while shaping engagement patterns.

Disciplinary Mediation of AI

Students' use of AI varies by disciplinary epistemology and language demands. Hard disciplines emphasize structured presentations, whereas soft disciplines focus on interpretive complexity and critical thinking (Biglan 1973; Stoecker 1993).

Hard-discipline students view AI as a functional assistant enhancing efficiency (Wang et al. 2024; Guidroz et al. 2025). Soft-discipline students require semantic interpretation and multi-perspective analysis, but AI often favors statistical patterns over critical contextual understanding, risking misinterpretation (Shi-xu 2024; Fan et al. 2024).

Effective AI integration requires alignment with disciplinary epistemic logic. When knowledge form, strategy, and cultural belief align, AI empower learners rather than act as a generic tool.

Integrating CLT and SDT

Recent years have seen a noticeable shift in research toward exploring AI-assisted reading in EFL contexts. For instance, Huang et al. (2025) developed a personalized two-tier problem-based learning model integrated with generative AI, which significantly improved university students' reading performance, motivation, and collaborative engagement. Similarly, Alazemi (2024) demonstrated that AI-driven formative assessment through the Nearpod platform enhanced reading comprehension, academic enjoyment, and self-regulation among EFL learners. These studies reflect an emerging focus on AI's capacity to scaffold complex reading processes, moving beyond generic text simplification. However, while promising, such work often targets general reading outcomes and provides limited insight into the underlying cognitive-motivational mechanisms.

Building on AI's dual cognitive-motivational functions and their modulation by disciplinary contexts, we propose an integrative framework combining CLT and SDT. This frames AI as dynamically balancing cognitive simplification and motivational activation, enhancing autonomy and competence.

Although recent contributions have begun to explore AI-assisted reading (e.g., Huang et al. 2025; Alazemi 2024), the field remains dominated by research on productive skills such as speaking and writing, with far less attention to receptive skills and their component subskills (Crompton et al. 2024). Their systematic review further highlights that existing studies seldom address the subskills necessary for comprehensive language proficiency, such as inferencing, critical evaluation, and discipline-specific vocabulary integration. Addressing this gap, this study examines how AI supports discipline-specific academic reading subskills in EFL higher education through the CLT-SDT lens, moving beyond generic skill improvement to strategically reduce cognitive load, foster autonomy, and strengthen subskill development across disciplines.

Methodology

Research Design

This qualitative study explored how generative AI influences academic reading motivation, engagement, and strategy use among Chinese EFL university students. It addressed a gap in disciplinary AI research (Maguire, Reynolds, and Delahunt 2020) by examining the impact of epistemological differences between hard/pure and soft/applied disciplines (Biglan 1973) on cognitive and motivational responses (Gao 2020; Nergis 2013). It received ethical approval from the Research Ethics Committee of Chengdu University. All participants provided informed consent with assurances of anonymity and voluntary participation.

Participants

Students at the University of Hong Kong with prior experience using generative AI to support academic reading were first invited to complete an open-ended questionnaire. We received 52 submissions; after eligibility and quality screening, 46 valid responses (88.5%) were retained for analysis. Responses were excluded if the respondent was not an EFL learner, did not specify their field/major, or provided incomplete answers. The retained sample spanned programs across Biglan's hard/soft and pure/applied dimensions, enabling analysis of disciplinary influences on AI use, motivation, and strategy adaptation. Demographic characteristics and the distribution of disciplines are reported in Table 1 and Table 2.

Category	#	%
Gender		
Male	16	35%
Female	30	65%
Age		
17-23	44	96%
24-30	2	4%
AI-Assisted Reading Frequency		
Always (more than three times)	8	17%
Often (three times per week)	27	59%
Sometimes (once or twice per week)	10	22%
Never	1	2%
Disciplinary Dimension One		
Applied	19	63%
Pure	11	37%
Disciplinary Dimension Two		
Hard	13	36%
Soft	17	64%

Table 1. Demographic information and Basic Information (The 46 participants reported 30 majors in total.)

	Applied	Pure
Hard	Computer Science Industrial Engineering and Logistics Management Environmental Science Quantitative Finance Actuarial Science Biomedical Engineering Pharmacy Applied AI Control Theory and Science	Neuroscience Biochemistry Math Physics
Soft	Business Administration Global Management Journalism Law Accounting Finance Economics Landscape Architecture Product Design Speech therapy	Criminology Cognitive Science General Linguistics Philosophy Sociology Chinese Study Psychology

Table 2. Subject classification based on Biglan's Disciplinary Dimensions

Data Collection

Data collection used a sequential mixed-methods design. Before collecting data, a simple informed consent form was delivered to participants to explain the main purpose of the study and their voluntary participation. An open-ended questionnaire gathered participants' general views on generative AI's benefits, challenges, and motivational effects. Follow-up semi-structured interviews with 32 students ensured disciplinary diversity and deepened thematic insights. The interview sessions were held in two virtual interview platforms (Tencent Meeting and Zoom). The average interview duration is 25 minutes. With the interviewees' consent, all interview sessions were recorded for transcription.

Data Analysis

Using MAXQDA, data from questionnaires and interviews underwent hybrid thematic analysis. To maximize the reliability of the analysis and the outcomes, researchers underwent three stages of data analysis, namely preparation, deductive coding and inductive coding. In the preparation stage, researchers deeply engaged with Table 1 to obtain an overall understanding of the responses offered by participants. Subsequently, we applied deductive coding to tag segments relating to pre-defined theoretical constructs based on SDT (Ryan and Deci 2000) and CLT (Sweller 1988). Then, inductive coding was employed to capture emergent themes arising directly from participants' responses, such as perceptions of AI's impact on reading autonomy. Double-coding ensured over 85% consistency. Iterative code refinement and memoing supported multi-level interpretation of AI's mediation of task complexity and learner agency.

Trustworthiness and Rigor

Credibility was ensured through method triangulation, member-checking, reflexive memoing, and continuous saturation monitoring (no new themes after 25 interviews). An audit trail documented coding and analytic decisions to enhance transparency and replicability.

Findings

These findings are not only relevant to understanding learner cognition but also provide actionable insights for AI-assisted reading system design, such as adaptive prompt complexity control, discipline-specific content annotation, and autonomy-preserving feedback mechanisms.

Disciplinary Modulation of Cognitive Load

This section addresses the investigation of RQ1. AI' s cognitive load effects in EFL reading are strongly moderated by disciplinary paradigms, creating distinct benefits and drawbacks in pure/applied and hard/soft disciplines. In pure and hard domains, where the knowledge system is highly structured and symbolized, learners' intrinsic load chiefly derives from disciplinary frameworks and logical inference. Therefore, more students consider AI as an interactive tool to ask questions, and those in hard disciplines mentioned the most cases (see Table 3). In these disciplines, AI's multi-contextual examples are more likely to add extraneous load, encouraging students to rely on traditional analytical tools. Among all student reported cases with increased extraneous load, readers in the field of pure and soft reported the most (see Table 4). As one math major student remarked:

> "Before the advent of AI, I already used dictionaries to address vocabulary shortages. Those methods were sufficient, making the prompt engineering required for AI interactions overly cumbersome."

Conversely, in applied and soft fields, knowledge systems are more pluralistic and open, so intrinsic load often arises from terminological polysemy and metaphors in the readings. To alleviate these difficulties, we find that students in both fields report a comparable more use of AI for terminology than those in pure and hard disciplines (see Table 3). Many students mention that AI effectively reduces this burden by offering multi-angle examples and diverse contextual annotations. As an example, a criminology student commented:

> "My English foundation is average; AI can largely help me decompose complex sentences. Many criminology texts employ numerous sociological definitions and explanations in lengthy sentences. Some terms carry different interpretations. AI translation or summarization can quickly identify key terms for me to digest."

Some respondents also noted that AI remains one-sided when handling deep cultural content. One participant shared:

> "Once, AI simply defined 'dark matter' as 'invisible matter,' I didn't notice distinctions from 'antimatter.'"

Accordingly, students adopt strategic corrections such as returning to the original text, cross-verifying outputs, and applying critical scrutiny. These strategies could also support deeper understanding of reading materials. We find that students in all four disciplines report increased germane load after using AI (see Table 4).

> A computer science major student shared that " (after using AI), I understand better now. For example, if there's a small detail hidden deep within the article that's hard to find, AI can find and explain it instantly."

By integrating Biglan's disciplinary classifications with Sweller's CLT, we find that the cognitive load effect of AI in EFL reading varies across subject paradigms. It may increase extraneous load, reduce intrinsic load, or promote germane load and deepen understanding through students' strategic use of AI. In the following session, we will further explore the effect of students' use of AI.

	Applied	**Pure**	**Hard**	**Soft**
Total report	**28**	**15**	**16**	**27**
Loop up Terms	50%	33%	25%	56%
Understand long and complex sentences	50%	40%	44%	48%

Add background information	61%	47%	69%	48%
Summaries and extract key points	82%	80%	81%	81%
Ask interactive questions	57%	53%	75%	44%

Table 3: Use of AI in different disciplines (Percentage)

Cognitive Load	Applied	Pure	Hard	Soft
Intrinsic ↑	11%	13%	0	19%
Intrinsic ↓	89%	100%	94%	93%
Extraneous ↑	46%	67%	44%	63%
Extraneous ↓	61%	67%	69%	59%
Germane ↑	82%	67%	75%	78%
Germane ↓	32%	27%	13%	41%

Table 4: Impact of AI Use on Cognitive Load (percentage)

Efficiency, Identity, and Motivation

In this section, we will examine the evidence and insights corresponding to RQ2. AI boosts short-term engagement and reading efficiency but risks superficial understanding and an illusion of competence that undermines sustained learning. Many students reported that AI use indeed lowers the comprehension barrier and increases willingness to engage. For instance, one student noted that using AI "helps me continue reading because it saves reading time and makes it less likely that I will give up."

Another commented:

> "AI recommendations based on my interests and difficulties enable me to arrange my study rhythm more reasonably, improving my autonomy and efficiency."

Students also highlighted AI summaries' role in guiding their reading decisions:

> "AI, by quickly summarizing, provides the broad framework and key points of the content, letting me know whether it contains what I need to decide if I should continue reading."

Students in all disciplines reported that AI increased their germane load (Table 4), which depends on active meaning-making. However, AI's oversimplifications and direct answers can lead to shallow processing and hinder systematic knowledge construction. One participant explained:

> "I found that for content in our own field, I initially look up many words in a dictionary, but over time I speed up and look up fewer. If I always rely on AI…I cannot really get to grips with it!"

Some students reported that summaries encouraged premature disengagement:

> "I feel that by reading the AI's summary, I have already learned the content of the article, so I choose not to continue reading."

These outcomes can be interpreted through two intertwined pathways. Firstly, the cognitive substitution pathway, shows how AI replaces active processing, depriving learners of opportunities to build knowledge structures and accumulate successful experiences, leading to an illusion of competence (Bandura 1997; Rozenblit and Keil 2002) and eroding self-efficacy, consistent with SDT's need erosion (Ryan and Deci 2017). Secondly, the motivational alienation pathway, reflects overreliance on external regulation, undermining autonomy and reducing initiative and engagement depth.

Socioculturally, Bourdieu and Johnson's (1993) concept of cultural capital explains variation. Students with stronger digital literacy and epistemic agency use AI selectively to reinforce rather than replace interpretation. Overall, AI's efficiency gains come at the cost of potential identity risks and motivational distortions, highlighting the need for scaffolds that fade progressively to support the transition from AI-assisted to autonomous learning.

AI, Interaction, and Cognitive Load

The following section systematically investigates the answers to RQ3. AI's impact on relatedness is dual patterned, comprising social facilitation and social substitution effects. Social facilitation occurred when AI-supported cognitive offloading enhanced learners' confidence and promoted collaborative engagement. For instance, one student reported:

> "One of our group members used an AI tool to summarize the case's key points…The entire discussion went smoothly; we all agreed with the AI's suggestions and then added our own ideas,"

indicating that AI-enabled preprocessing not only optimized group efficiency but also activated deeper co-construction of meaning. Another student reflected:

> "With AI, I feel more confident in my comprehension, so I participate more in offline interactions,"

suggesting that AI tools may bolster social initiative by reducing comprehension anxiety and strengthening perceived competence. These findings align with SDT's proposition that contextual support can indirectly fulfill relatedness needs through enhanced self-efficacy (Ryan and Deci 2017).

In contrast, a social substitution effect was observed when the convenience of AI prompted students to bypass human-mediated knowledge construction. Several participants reported decreased help-seeking from instructors and peers as AI supplanted traditional interpersonal scaffolding. To compensate, some students deliberately included more personal reflections in discussions to maintain academic legitimacy.

Meanwhile, a contrasting group demonstrated enhanced social responsiveness due to reduced reading load. One student noted:

> "Before tutorials, if you hadn't finished reading an article, you wouldn't ask questions. But now, with AI… I can complete readings before class, and I actually

welcome my tutor's questions, and even when discussing with classmates, I feel very confident."

This suggests that AI-mediated efficiency may, in some cases, amplify learners' desire for interaction, fostering new forms of engagement.

Collectively, these findings highlight the ambivalent nature of AI's impact on relatedness: while AI can either displace or stimulate social behaviors, its effects are not linear but mediated by learner strategies, identity concerns, and interactional contexts. Our findings suggest that pedagogical designs must address both cognitive-resource liberation and social-resource reconstruction to prevent efficiency gains from undermining interpersonal richness. Designing AI-assisted tasks with embedded interactional affordances and metacognitive scaffolds may help learners navigate the efficiency-engagement tension and achieve meaningful connectedness. To enhance the translational value of the findings for AI-assisted reading system design, we mapped each empirically derived mechanism to potential AI affordances and functional modules. This mapping does not prescribe fixed system architectures but illustrates how qualitative insights can inform the design of adaptive, discipline-sensitive AI reading environments.

Discussion

This study reveals the complex interaction between generative AI's regulation of cognitive load and dynamics of learning motivation in EFL academic reading. Drawing on Biglan's disciplinary dimensions (1973), Self-Determination Theory (Ryan and Deci 2000) and Cognitive Load Theory (Sweller 1988), interrelated pathways are identified to elucidate the underlying mechanisms through which AI both facilitates and hinders academic reading outcomes (Figure 1).

Disciplinary paradigms shape how students perceive and use AI language support. In soft and applied fields, text may bring additional cognitive loads due to unclear language or logic. Prior research shows that students in humanity fields are largely benefit from AI's text summarization, language translation, and historical retrieval (Sun et al. 2025). We further investigate AI's impact on EFL readers' cognitive load. AI relieves students' cognitive burden, supporting them to explain and interact with text more deeply. Hard and pure fields have high intrinsic cognitive loads due to dense symbols and abstract ideas. For these students, AI plays a role in reducing the need to decode text and formulas, simplifying learning and reading process. A recent study shows that many STEM students directly use AI-generated solutions for coursework, which creates a false sense of mastery while undermining their deep learning (Wang et al. 2025). This pattern can also be found in the context of EFL reading. Participants reported that AI-assisted reading may increase their extraneous cognitive load, resulting in surface-level understanding and pseudo-competence in reading.

These findings also resonate with emerging concerns about digital literacy in AI-mediated learning. It decides if students check AI outputs thoughtfully and manage their own learning, or become passively dependent on AI (Bauer et al., 2025). In exploratory research on Chinese undergraduates, researchers found that all students make critical reflection on AI generated information (Xiao and Zhi 2023). Our findings resonate with it. After using AI, many students reported consciously check and strategic corrections. For instance, a journalism student noted that although AI enhances retrieval efficiency, he cross-checks outputs with original texts, showing how disciplinary background and metacognitive skills jointly shape effective AI use.

Although AI promotes cognitive offloading, it also carries risks of autonomy loss. In another research, EFL AI users reported over-reliance on technology decreases thier competence and sense of achievement as they attribute their success to AI (Wang and Wang 2024). Our research further demonstrates how students deal with this situation. They exhibit strategic autonomy by restricting AI use to specific contexts and engaging in reflective verification to maintain cognitive control and autonomy. Educational practice should adopt an AI-use grayscale principle, clearly defining AI intervention boundaries and integrating reflective activities to foster metacognitive development.

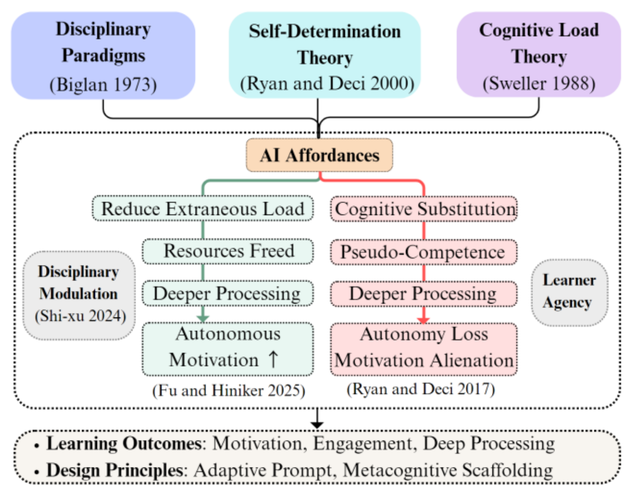

Figure 1: AI-Assisted Reading: Cognitive and Motivational Pathways and Disciplinary Modulation.

In summary, the application of generative AI in EFL academic reading must fully consider disciplinary paradigm differences and individual digital literacy levels, balancing cognitive load, motivational states, and social interaction tensions. Practical guidelines for curriculum design and AI system development emerge from these findings.

Practical Translation for AI in Education

Building on preceding analysis, present findings can be directly transferred to strategies for both EFL teachers and AI system developers, thereby extending the study's theoretical contributions into deployable educational innovations.

Across all disciplines, it is significant for teachers to guide students for verification and correction of AI outputs and personal reflection in assessment. To balance efficiency with reading depth, instructors could require students to declare the scope of AI use and their verification procedures. Disciplinary differences also play a role. In a study on policies in US higher education regrading Gen AI, researchers found an imbalance in the guidance received by students from different disciplines (McDonald et al. 2024). For curriculum designers, embedding AI tools with interaction designs tailored to different disciplinary contexts can better align cognitive and motivational affordances. To be more specific, in soft and applied fields, AI could be applied before class to generate term or culture check tasks for students to return to the original text for verification. In class, teachers may first use AI to decompose long sentences and map discourse relations, then invite students to reconstruct the logic in their own words and annotate causal or contrastive relations to check their understanding. In hard/pure fields, instructors may permit AI to supply formal definitions, key constraints, and minimal hints; However, derivations must be produced by students. We suggest the use of AI to be limited to step-level diagnostics and checks.

AI tool developers may focus on providing adjustable discipline-specific modes to protect users' autonomy. For instance, for soft and applied users, load reduction may be prioritized. AI could deliver semantic disambiguation and metaphor or slang explanations in the form of original sentence, gloss and comparable contexts. It is helpful if AI supports in-document sentence decomposition and term glossing. In the mode for hard/pure students, AI could focus on preserving users' reasoning, instead of substituting. This includes symbol and boundary checks, step-level error categorization, and minimal next-step hints. Aside from that, developers are advised to include features that protect learner autonomy, such as options for adjustable assistance levels. Delayed hints and embedded reflective prompts would also play a role in lowering the risk of over-reliance. They help prevent students from outsourcing their thinking, enhancing readers' understanding.

Limitations and Future Directions

This study has several limitations that constrain the generalizability of its findings and the immediacy of the proposed AI-assisted reading design principles. First, the sample comprised 46 Chinese EFL students from a single elite institution (the University of Hong Kong). Despite disciplinary diversity, external validity is limited, and future work should recruit larger, multi-site cohorts spanning elite and non-elite universities and different regions to enable robust cross-context comparisons. Additionally, The gender imbalance in this study's sample may lead to an inadequate estimation of gender effects, preventing a clear determination of whether gender influences the outcomes. Third, the qualitative design relied mainly on self-reported data, which may introduce bias despite triangulation, and lacked behavioral or observational data that could better capture real-time AI interactions. Future studies could combine qualitative accounts with multimodal behavioral measures (e.g., learning analytics, eye-tracking, or LLM log data) and outcome assessments. Furthermore, the absence of baseline constrains causal claims. Future researchers could design quasi-experimental or randomized designs with pretest–posttest baselines and appropriate comparison conditions to isolate the effects of specific AI features. Lastly, as the sampling frame was restricted to Chinese EFL learners, limiting generalizability to other sociolinguistic contexts. Thus, comparative studies across regions, language backgrounds, and educational systems are warranted. Given these constraints, the design principles advanced in this paper should be further validated before broad adoption.

Conclusion

This study investigated the interplay between cognitive load regulation and motivational dynamics in AI-assisted academic English reading among Hong Kong EFL learners, framed by Cognitive Load Theory and Self-Determination Theory. While generative AI effectively reduced extraneous cognitive load through text simplification, its impact on motivation varied by disciplinary context. Learners in soft and applied fields engaged in deeper semantic processing, whereas those in hard/pure disciplines primarily leveraged AI for surface-level processing. Notably, excessive reliance on AI fostered illusory mastery and diminished self-regulatory engagement. Digital literacy and metacognitive awareness moderate these effects by enabling critical reflection on AI outputs. Additionally, AI reshaped social interactions by reducing routine exchanges but facilitating higher-order collaboration when appropriately integrated. These findings underscore the necessity of instructional designs that balance cognitive efficiency with fostering learner autonomy and critical engagement aligned to disciplinary epistemologies. In doing so, the research advances understanding of AI's cognitive-motivational mechanisms and informs the AI for Education agenda through discipline-specific design principles and targeted AI literacy guidelines. It offers a concise roadmap for creating sustainable, autonomy-preserving AI-assisted learning environments.

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