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Understanding GenAI-Assisted English Learning Among College Students: A TAM- and SRL-Based Interview Study

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Abstract

This study examines how college students use generative AI for English self-regulated learning. 16 undergraduates were interviewed using semi-structured protocols. Data were analyzed via hybrid thematic analysis using NVivo 11. The results reveal three usage frequencies: frequent (31.25%), occa-sional (43.75%), and on-demand (25%). Translation (87.5%) and writing assis-tance (75%) were primary uses, while listening training was unused. Although all participants valued AI for improving efficiency and output quality, over half ques-tioned its long-term developmental impact and expressed concerns about shal-low content and over-reliance. AI effectively supported monitoring and reflection (62.5% engagement) but rarely aided learning planning (18.75%). Key barriers included inaccurate outputs (62.5%) and challenges in formulating precise prompts (56.25%). Attitudes toward academic integrity varied, with most con-sidering the line between assistance and cheating as purpose-dependent. This study offers nuanced insights into generative AI integration in language learning and suggests implications for optimizing AI-supported educational practices.

Keywords

Generative AI; self-regulated learning; technology acceptance

1. Introduction

The rapid advancement of generative artificial intelligence (GenAI) has reshaped contemporary education, unlocking new potentials for language acquisition. Powered by large language models, GenAI tools (e.g., ChatGPT, DeepSeek, Gemini) can provide timely, context-sensitive responses, facilitate meaning negotiation, and offer nuanced language feedback—distinguishing themselves from traditional computer-assisted language learning technologies by enabling personalized interaction, interactive explanations, and multi-turn dialogue rather than merely delivering pre-programmed content (Benotti et al., 2018[1]). These affordances support learners in externalizing cognitive processes, testing hypotheses, and simulating real-world communicative tasks. Given its educational prospects, scholars have increasingly focused on GenAI's pedagogical effects, exploring themes such as academic achievement (Kim & Lee, 2023[11]; Sun & Zhou, 2024[23]), motivation (Hong et al., 2016[8]; Lee et al., 2022[13]), learning attitudes (Chan & Hu, 2023[3]; Lee et al., 2022[13]), and self-efficacy (Fryer et al., 2020[7]; Ren, Guo & Li, 2025[20]).

Parallel to technological progress, self-regulated learning (SRL), defined as learners' proactive capacity to manage complex learning activities (Zimmerman & Schunk, 2011[21]), has gained growing recognition in educational psychology and language learning research. SRL is critical to academic success (Kizilcec et al., 2017[12]), as successful learners engage in cyclic forethought, performance, and self-reflection rather than merely responding to external instruction (Pintrich, 2000[18]; Zimmerman, 2002[27]). This multi-dimensional construct (encompassing motivational, cognitive, metacognitive, and behavioral factors) is particularly vital in foreign language learning, where proficiency development requires sustained effort, gradual progress, and delayed feedback. For university students, mastering a foreign language involves long-term vocabulary accumulation, grammar consolidation, and communicative competence cultivation, which are the processes that are easily hindered by ineffective self-regulation, leading to reduced motivation and inefficient learning.

Despite its significance, SRL remains challenging for many learners, especially in teacher-centered educational contexts with limited autonomous learning opportunities. Similar to Japanese EFL students (Falout et al., 2009[6]), Chinese undergraduate EFL learners often experience anxiety and low motivation (Liu, 2009[15]), as English learning is tied to high-stakes examinations (e.g., CET-4/6) linked to graduation and further study. This exam-driven paradigm overemphasizes performance outcomes over metacognitive development, leaving students with insufficient SRL strategy training. Additionally, foreign language anxiety, low confidence, and inadequate feedback mechanisms further impede effective self-regulation. Thus, exploring how modern tools like GenAI can support SRL in this context holds important theoretical and practical value.

GenAI has emerged as a promising mediator for SRL in foreign language learning, offering immediate, dialogic, and individualized support aligned with key SRL phases: assisting with task performance (e.g., translation, writing revision, vocabulary practice) and facilitating reflection (e.g., error evaluation, strategy refinement). These affordances may reduce cognitive load, enhance metacognitive monitoring, and boost autonomous learning behaviors. However, empirical research on how GenAI supports SRL in foreign language contexts remains limited—existing studies often focus on tool adoption or learner attitudes rather than exploring how learners leverage GenAI for self-regulation outside formal classroom settings. Few studies have specifically addressed the Chinese higher education context, where GenAI adoption among EFL students has expanded rapidly without systematic instructional guidance.

This study aims to fill these gaps by examining how GenAI supports self-regulated foreign language learning among Chinese undergraduates. It contributes to broader discussions on learner autonomy in the AI era, evolving learning strategies, and reconfigured teacher-learner-tool relationships in foreign language education. The findings will also provide actionable insights for educators and policymakers to better empower learners through GenAI.

2. Literature Review

2.1. Self-Regulated Learning Theory

SRL is a key framework in educational psychology, focusing on learners' active management of cognitive, motivational, and behavioral processes to achieve goals. It includes setting objectives, monitoring progress, and adapting strategies based on feedback (Panadero, 2017[17]). Six major models, by Zimmerman, Boekaerts, Pintrich, Winne, Efklides, and Hadwin, share cognitive, metacognitive, behavioral, motivational, and emotional elements, depicting SRL as a cyclical process: forethought (planning), performance (monitoring), and self-reflection (evaluation).

Zimmerman's model draws on social cognitive theory, influenced by personal, behavioral, and environmental factors (Zimmerman, 2002[27]). Boekaerts emphasizes motivational pathways from contextual appraisals, while Winne and Pintrich highlight feedback loops (Boekaerts, 1997[2]). Recent work extends SRL to digital contexts, integrating sociocultural perspectives with theories like expectancy-value and achievement goals (Sugimoto, 2023[22]). Meta-analyses confirm SRL's positive impact on academic performance, though overlaps call for context-specific studies, especially in technology-enhanced language learning where it builds autonomy and resilience (Panadero, 2017[17]; Zimmerman, 2002[27]).

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), rooted in the Theory of Reasoned Action, predicts technology adoption via perceived usefulness (performance enhancement) and perceived ease of use (effort required), shaping attitudes and intentions (Davis, 1989[5]). Extensions like TAM2 and TAM3 add variables such as subjective norms and job relevance (Venkatesh & Bala, 2008[24]). In education, TAM integrates with UTAUT, incorporating performance expectancy, social influence, and facilitating conditions for e-learning evaluation.

Reviews note the simplicity of TAM but critique its determinism and neglect of individual factors (Martin, 2022[16]). In language learning, it assesses digital tools, often extended with self-efficacy and enjoyment. Meta-analyses affirm its robustness, though hybridization with other models is recommended for complex behaviors, including AI integration (Martin, 2022[16]).

2.3. AI-Assisted Self-Regulated Language Learning

AI-assisted SRL in language learning uses tools like chatbots and generative AI (GenAI) for personalized feedback, adaptive resources, and progress monitoring across SRL dimensions (Chang & Sun, 2024[4]). AI acts as dynamic partners, enhancing engagement, vocabulary, and speaking skills; VR reduces anxiety via tailored practice (Qiao & Zhao, 2023[19]). Meta-analyses show strong effects on forethought and reflection, moderate on cognition and motivation, but inconsistent on behavior, with risks like over-dependence (Chang & Sun, 2024[4]).

In China, AI targets EFL learners, improving pronunciation, coherence, and motivation through tools like ChatGPT (Qiao & Zhao, 2023[19]). It fosters grit and flow, aligning with self-determination theory. In schools, adaptive AI boosts engagement, though metacognitive prompts need refinement; GenAI literacy mediates SRL via needs satisfaction (Zhang et al., 2024[26]). East Asian focus aids equity, but ethical concerns persist.

Although extensive research has established SRL as a cyclical framework enhancing autonomy in language learning (Panadero, 2017[17]; Zimmerman, 2002[27]) and TAM as a robust predictor of technology adoption in educational contexts (Davis, 1989[5]; Venkatesh & Bala, 2008[24]), with AI tools increasingly integrated to support SRLL dimensions (Chang & Sun, 2024[4]; Qiao & Zhao, 2023[19]; Zhang et al., 2024[26]), significant gaps remain. Most studies rely on experimental designs, large-scale surveys, or pre-2022 AI applications, often overlooking real-world, non-experimental GenAI use among Chinese EFL learners, post-ChatGPT prompt engineering barriers, nuanced ethical/dependence issues, and qualitative insights into SRL-TAM hybrids in everyday autonomous settings. This study addresses these by conducting semi-structured interviews with 16 Chinese college students to explore GenAI's usage patterns, acceptance, SRL performance, barriers, and ethical perceptions, providing context-specific, user-centered evidence to bridge theoretical models with practical EFL dynamics.

3. Method

3.1. Participants

Altogether 16 undergraduate students (freshmen-seniors) were recruited in this study. They were from varied majors who had prior experience using generative AI tools (e.g., ChatGPT, DeepSeek, Doubao) for English autonomous learning. Inclusion criteria required (a) current university enrollment, (b) self-reported prior use of at least one generative AI tool for English learning, and (c) willingness to be recorded. Recruitment was carried out via campus announcements and instructor referrals to achieve heterogeneity in major, proficiency, and AI-usage frequency. Ethical approval was obtained and all participants provided informed consent; participation was voluntary and anonymized.

3.2. Data Collection

Data was collected through semi-structured interviews conducted in four parallel interview groups (i.e., four consecutive batches of individual interviews using the same protocol) to allow consistent comparison while accommodating scheduling. Each interview was a group with four students, lasted about 45 minutes. The interview protocol comprised open-ended questions and probes mapped to TAM constructs and SRL components.

3.3. Data Analysis

After each interview, the research team would convert the audio recording into text using speech transcription software. Then the transcribers would review the transcribed text sentence by sentence to ensure accuracy. During the data analysis phase, this study employed a hybrid thematic analysis approach that combined deductive and inductive reasoning. Initially, a priori coding framework was constructed based on the TAM and SRL. Systematic coding was then conducted using the qualitative data analysis software NVivo 11. While coding was theoretically informed, we remained open to the data, capturing and integrating new themes that emerged organically from the interviews.

To ensure the trustworthiness of the research, upon the completion of preliminary analysis, selected participants were invited to review the findings to confirm that their intended meanings were accurately represented. Their feedback was incorporated to refine the interpretations; a peer researcher who was not involved in this study was invited to scrutinize the data analysis process and logical reasoning. This served to challenge potential researcher biases and provided an external audit trail.

4. Result

4.1. Usage Behavior of GenAI-Assisted English Autonomous Learning

Participants exhibited stratified GenAI usage frequencies: 31.25% (5/16) used it frequently (daily/regular integration), 43.75% (7/16) occasionally (assignments/difficulty resolution), and 25% (4/16) on-demand (exam/thesis preparation), with no non-users. Core usage purposes were task-oriented (Table 1), dominated by translation (87.5%, 14/16) and writing assistance (75%, 12/16), followed by vocabulary learning (56.25%, 9/16), text structure analysis (37.5%, 6/16), and oral practice (18.75%, 3/16); no use for listening training was reported. Temporally, 68.75% (11/16) used GenAI ad-hoc for problem-solving, 18.75% (3/16) at fixed frequencies (e.g., weekly essay revision), and 12.5% (2/16) via fragmented time (vocabulary review/short translation); no participants allocated dedicated time for AI-assisted learning (see Table 1).

Table 1. GenAI usage frequencies

Usage Purpose	Proportion (n=16)
Translation (text/sentence/word)	87.5%(14/16)
Writing assistance (correction/polishing/ideation)	75%(12/16)
Vocabulary learing (synonym/context/example)	56.25%(9/16)
Text structure analysis	37.5%(6/16)
Oral practice	18.75%(3/16)
Listening training	0%(0/16)

4.2. Technology Acceptance: perceived Usefulness (PU) and Ease of Use (PEOU)

All participants (100%) recognized GenAI's efficiency superiority. Specifically, 81.25% (13/16) noted time savings in information retrieval, and 62.5% (10/16) reported reduced repetitive work. Seventy-five percent (12/16) experienced improved output quality (authentic expressions: 68.75%; fewer grammatical errors: 50%), though 31.25% (5/16) criticized content shallowness and lack of individuality. Only 37.5% (6/16) perceived long-term ability enhancement; 62.5% (10/16) deemed gains non-intuitive, and 18.75% (3/16) worried about weakened independent thinking from over-reliance.

Regarding PEOU, 87.5% (14/16) found GenAI easy to operate for basic functions (translation/vocabulary inquiry). However, 56.25% (9/16) faced advanced barriers (imprecise prompting, contextual incoherence in follow-ups), and 31.25% (5/16) reported technical issues (slow loading/crashes).

4.3. SRL Performance

SRL performance varied across dimensions: Only 18.75% (3/16) used GenAI for learning planning, with most (81.25%) preferring self-arrangements due to GenAI's poor adaptability to short-term changes. In monitoring/reflection, 62.5% (10/16) actively analyzed AI feedback, while 37.5% (6/16) were result-oriented. Seventy-five percent (12/16) distinguished learning from copying (68.75% completed tasks independently first; 56.25% requested AI reasoning explanations), though 25% (4/16) directly used AI outputs for non-core tasks. For motivation regulation, 50% (8/16) maintained learning continuity, and 37.5% (6/16) reduced help-seeking anxiety; conversely, 43.75% (7/16) reported no interest improvement, and 12.5% (2/16) experienced illusory mastery anxiety.

4.4. Usage Barriers and Support Needs

Key barriers were inaccurate content output (62.5%, 10/16), difficulty formulating precise prompts (56.25%, 9/16), technical instability (31.25%, 5/16), information overload (18.75%, 3/16), and network dependence (12.5%, 2/16). Support needs focused on three areas: prompt engineering training (56.25%), AI functional optimization (68.75%, e.g., personalized planning, oral interaction), and institutional resource integration (37.5%).

4.5. Ethical Cognition, Dependence, and Social Influence

Regarding academic integrity, 37.5% (6/16) fully accepted AI-assisted thesis writing (AI drafting + manual revision), 50% (8/16) conditionally accepted AI for ideation, and 12.5% (2/16) opposed it; 75% (12/16) linked the assistance-cheating boundary to usage intent. For dependence, 43.75% (7/16) admitted moderate reliance, 56.25% (9/16) maintained independence, and 18.75% (3/16) reduced usage periodically. Socially, 68.75% (11/16) reported teachers' neutral attitudes, 25% (4/16) noted teacher support for auxiliary use, and 81.25% (13/16) were unaffected by peer behavior.

5. Discussion

The findings show that GenAI was predominantly used on-demand for practical, output-oriented tasks such as translation (87.5%) and writing assistance (75%) dominated, while oral practice (18.75%) and listening training (0%) were largely neglected. This aligns with prior studies highlighting GenAI's strength in form-focused tasks (Chang & Sun, 2024[4]; Li et al., 2025[14]) but contrasts with experimental research reporting holistic skill development under structured instruction (Qiao & Zhao, 2023[19]). The discrepancy stems from the exam-oriented EFL context in China: learners prioritize test-score improvement over comprehensive skill building, and current GenAI tools lack real-time interactive functions for oral and listening practice. Most learners (68.75%) used GenAI reactively to solve immediate problems rather than proactively integrating it into study routines, reflecting its role as a situational tool rather than a comprehensive learning companion without pedagogical scaffolding.

The results strongly support TAM's core assumptions (Davis, 1989[5]; Venkatesh & Bala, 2008[24]): all learners recognized GenAI's efficiency advantages, and 87.5% deemed basic operations easy to perform. Learners valued GenAI for time-saving information retrieval and reduced repetitive work, which aligns with prior TAM-based educational technology research. However, TAM's limitations are also evident: 31.25% criticized GenAI-generated content for shallowness and lack of individuality, and only 37.5% believed it boosted long-term ability. These reservations echo Martin's (2022)[16] critique that TAM overlooks learning depth, as effective advanced GenAI use requires prompt engineering skills that 56.25% of learners lacked. This expands TAM by demonstrating that perceived usefulness is shaped not only by tool functionality but also by users' digital literacy.

The findings reveal a mixed performance of GenAI in supporting SRL: it moderately facilitated monitoring, reflection, and motivation regulation but played a limited role in planning and goal-setting. Only 18.75% of learners used GenAI for planning, as most preferred flexible personal arrangements due to the tool's poor adaptability to short-term changes, this diverges from meta-analyses reporting strong AI effects on planning under guided conditions (Chang & Sun, 2024[4]). In monitoring and reflection, 62.5% of learners actively analyzed AI feedback to optimize learning strategies, while 37.5% focused solely on results, reflecting a passive learning approach. For motivation regulation, GenAI exerted dual effects: it maintained learning continuity (50%) and reduced psychological barriers to asking questions (37.5%) but failed to boost intrinsic interest (43.75%) and even caused illusory mastery anxiety (12.5%). This underscores that GenAI addresses instrumental motivation but not the intrinsic motivation central to sustained SRL.

Key usage barriers included inaccurate content output (62.5%), difficulty formulating precise instructions (56.25%), and technical instability (31.25%). These reflect the interplay of tool limitations (e.g., large language model hallucinations), user literacy gaps, and environmental constraints. Learners' support needs (e.g., instruction training, functional optimization, and resource integration) provide actionable guidance for GenAI integration in EFL education. Training in task-specific prompt engineering can enhance learners' digital literacy; optimizing GenAI functions for personalized planning and oral interaction can fill current skill coverage gaps; and school-provided authorized AI tools can transform GenAI from an extracurricular aid to an in-class learning companion. These steps align with the human-AI collaborative learning model advocated by Qiao & Zhao (2023)[19], where technology complements teacher guidance.

Learners exhibited diverse attitudes toward AI-assisted academic writing: 37.5% fully accepted it, 50% conditionally accepted it for idea generation, and 12.5% firmly opposed it. Most viewed the boundary between assistance and cheating as dependent on usage purpose, highlighting the need for clear institutional guidelines. Regarding dependence, 43.75% reported moderate reliance, while 18.75% periodically reduced usage to avoid over-reliance, indicating that most learners maintained self-regulatory control. However, 25% directly copied AI-generated content for non-core tasks, signaling a risk of weakened critical thinking among learners with low SRL ability. This emphasizes the need for ethical use training alongside GenAI integration in EFL curricula.

6. Conclusion

This study investigated college students' use of generative Al in English autonomous learning through the combined framework of the TAM and SRL theory. The findings show that generative Al has been widely accepted and routinely integrated into students' learning practices, yet its pedagogical impact remains selective and inherently ambivalent. Students primarily employed Al as an efficiency-oriented auxiliary tool, especially for translation, writing assistance, and vocabulary learning. While they strongly acknowledged Al's advantages in saving time, reducing repetitive work, and improving surface-level linguistic accuracy, many expressed reservations about the depth, originality, and individuality of Al-generated content. Moreover, only a minority perceived AI as contributing directly to sustained language ability development, while many emphasized that meaningful improvement still hinged on independent practice and cognitive engagement.

From a theoretical perspective, the findings contribute to current understandings of AI-assisted language learning by highlighting the uneven role of generative AI across different dimensions of self-regulated learning. AI was more frequently used to support learning monitoring and reflection but played a limited role in learning planning and goal setting, with mixed effects on motivation regulation. More importantly, the results suggest that generative AI functions as a pedagogically ambivalent mediator rather than a uniformly empowering or detrimental force. By supporting monitoring and error correction, AI may partially shift regulatory control away from learners, raising questions about how self-regulation is developed and maintained in AI-supported autonomous learning.

From a practical and educational perspective, the findings indicate that the key challenge of generative AI lies not in whether it is used, but in how learning regulation and learning quality are managed and evaluated. As AI-assisted outputs no longer reliably signal learners' deep cognitive engagement or competence development, a growing process-product dissociation emerges. This challenges traditional product-oriented assessment practices and calls for pedagogical approaches that foreground learning processes, such as drafts, revision rationales, and reflective accounts of AI use. For both learners and teachers, effective AI integration therefore requires reflective engagement with AI feedback and instructional designs that help maintain learner agency and self-regulatory control.

Despite these contributions, this study has several limitations. The relatively small sample size and reliance on self-reported interview data limit the generalizability of the findings and focus primarily on learners' perceived experiences rather than observable learning behaviors or long-term language outcomes. Building on these limitations, future research may adopt larger-scale quantitative or mixed-method designs and longitudinal approaches that combine performance measures, learning analytics, and reflective data. Such research could further examine whether phenomena such as process-product dissociation persist across broader contexts and how pedagogically guided AI integration shapes learners' regulatory control, ethical judgment, and learning depth over time.

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