

A Study on Cultivating College English Learners' Autonomous Learning Ability Empowered by Artificial Intelligence

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Abstract

The new opportunities for college students to foster their autonomous learning ability have emerged with the rapid development of artificial intelligence (AI). This research examines how artificial intelligence tools can be incorporated into university English courses to strengthen students' ability to learn independently. Grounded on theories of SRL and learners' autonomy, this study is conducted with a mixed methods approach that involves 126 undergraduates who are not majoring in English at a finance and economics university located in southwest China. The quantitative results come from an instrument that was used to measure learners' autonomous behavior prior to and following a treatment where students engaged in an AI-based teaching session for sixteen weeks, while qualitative information was collected through semi-structured interviews of 12 purposefully selected students. Results show that there are statistically significant changes, before and after the intervention, regarding the student's perception about his/her goals, strategy use, self-monitoring and motivational regulation. Furthermore, the qualitative analyses showed that learners perceived the AI tools as an easily available tutor, as adaptive practice partners, and instant feedback providers, thus alleviating learners' apprehension and boosting their involvement in autonomous EL. The current work provides pedagogical implications to designing AI-integrated LACs and highlights risks of over-reliance on automated feedback. Due to the study's one-group pre-test and post-test design, we do not have clear-cut causality evidence to show that it was AI which caused this change, nor can we say that the behaviour changed is a permanent one.

Keywords

Artificial Intelligence, Autonomous Learning, College English, Self-Regulated Learning, Technology-Enhanced Language Learning, Mixed Methods

1. Introduction

Learner autonomy has always been considered an important product of university education, and is one of the major indicators for successful lifelong learning. In foreign language learning, self-study plays an especially crucial role because of limited in-class hours and continuous out-of-syllabus practice required to learn language well. In the last forty years, applied linguists have long contended that autonomy promotion ought to be the focus of language teaching, not an incidental product (Benson, 2011; Littlewood, 1996). Yet despite such agreement, developing true independence in large enrollment college composition classrooms continues to be an ongoing concern and issue for many instructors. Students often come to college having developed study habits that are dependent upon teachers from high school, and are unable to identify objectives, choose tactics, keep scorecards, or maintain self-discipline unless monitored closely by an overseer.

Artificial intelligence presents an arguably revolutionary solution to that problem. Artificial intelligence-augmented language learning software, smart tutors, automatic essay scoring systems can provide adaptive tasks, instantaneous feedback, flexible assistance in amounts that no single human instructor could provide (Zawacki-Richter et al., 2019). Recent progress on large scale language model also extends this possibility for interaction with learners to free text conversation, get feedback in the form of explanations that are on their-own-level and get customized recommendations about what they could do better (Kasneci et al., 2023). These advances prompt a key educational issue: how might we intentionally integrate these artificial intelligence systems into our college-level English classrooms to foster, rather than just complement, students' self-capacity?

In this paper, I tackle the issue with an empirical study on a College English class equipped with AI. The study has three goals: firstly, it examines if a smart-assisted instructional method has any impact on learners' autonomous learning behavior; secondly, it seeks to shed light on learners' perceptions about and uses for AI-based instruments in autonomous language learning; thirdly, it tries to uncover the pedagogical contexts within which integrating AI is most beneficial in promoting learner autonomy. Drawing from quantitative as well as qualitative information, the study provides an in-depth picture on how AI can facilitate the development of autonomous learning, as well as practical guidance to foreign language educators and syllabus designers. The limitations are pointed out in terms of causality due to lack of comparison groups.

The study is motivated by these timely trends toward student-centered instruction and rapid adoption of AI technology in education. While there have been studies focusing separately on student agency or artificial intelligence for education, few investigations have focused on examining the intersection between them in college English teaching. To fill this gap, the current work constructs and examines an instructional framework which employs artificial intelligence as a means of cultivating student self-direction instead of substituting for students' own agency.

2. Literature Review

2.1. Learner Autonomy in Language Education

Holec (1981), who gave formal recognition to the notion of learner autonomy in the field of applied linguistics by defining it as “the ability to take charge of one’s own learning.” Since then, the concept has been expanded and discussed in many works. Little (1991) emphasized on the psychological dimension of autonomy, defining it as “the capacity for stepping back, reflection, decision-making, and independent action”. Benson (2001) suggested a multidimensional concept including technical, psychological as well as political aspects of autonomy, whereas Littlewood (1996) differentiated active autonomy in which the learner sets his/her own aims, and reactive autonomy, when they control themselves in the execution of ways that accomplish goals given them by someone else.

The overwhelming evidence from a wide variety of studies suggests that students who control the direction and content of their instruction learn more effectively in acquiring languages, display more motivation, and persist longer in face of difficulty (Benson, 2011), but there has been evidence indicating that autonomy was not something intrinsic to students but could be cultivated through pedagogical intervention; Dickinson (1995) pointed out the strong connection between autonomy and motivation, noting that independent learners have greater intrinsic motivation, since they feel like they determine what and how much they learn; Butler (2002) went on to argue that the role of feedback is critical for fostering autonomy as it helps the student learn about evaluation criteria, thus becoming a better judge of her or his own work.

However, despite such theoretical progress, the cultivation of autonomy is not easy to achieve in actual practices. It has been found that in many learning environments, including Chinese universities, traditional teacher-centred pedagogy and examination-oriented learning cultures hinder the development of learner autonomy, where students have few opportunities for practicing their own direction in the formal curricula and instructors might be unsure about how to best scaffold autonomy in a way that doesn’t sacrifice content coverage. These on-the-ground challenges underscore the value of creative pedagogical strategies for consistently nurturing student autonomy.

2.2. Artificial Intelligence in Language Learning and Teaching

AI has been used in language instruction since the 1960s and initial efforts were devoted to ITS (Intelligent Tutoring Systems), computer adaptive testing, and natural language processing in grammar correction. The area exploded recently, driven by the advances of machine learning, big data and natural language understanding. Hwang and Tu (2021) defined AI-based educational applications as systems which can perceive learner’s state, reason about their needs and provide individualized response/recommendations. They defined a number of the important roles for AI to play in education, e.g., intelligent tutoring, adaptive assessment, learning analytics, or automatic content creation.

Zawacki-Richter et al. (2019), who conducted a systematic review of the literature about the application of artificial intelligence to higher education, which included 146 papers, classified them into four main domains: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. They found that AI has been not only applied successfully to improve the effectiveness of learning as well as its personalization but also been observed as an apparent dearth of reflective discussion about ethics and pedagogy. When it comes to language learning, in particular, AI tools have been applied to automatic essay scoring, speech recognition and articulation therapy, adaptive dictionary suggestion and conversational practice with chatbots.

A special case is the rise of large language models. Kasneci et al. (2023) claimed they could be used in general for educational purposes, explaining, exercising, grading, and conversing. At the same time, they warned against blind reliance on these technologies that leads to complacency, hampers reasoning, and fosters overconfidence in possibly wrong results. Such issues are particularly relevant for natural language understanding, where both the quality and the accuracy of the linguistic input are crucial to learning.

2.3. Technology-Enhanced Learner Autonomy

Researchers on CAI have explored how technology is related to learners' autonomy. Early researches proposed that technology may support learners' autonomy because it allows them to have more access to materials, as well as more control over pace and contents. Wang (2022) reviewed TELL systematically and observed that good-designed technologies will be able to support students' participation, strategy use, and self-regulation. Nevertheless, as was pointed out in this review, it must be emphasized that technology by itself does not suffice to foster autonomy and that well-considered pedagogical designs which integrate tools together with explicit instruction of strategies and meta-cognition are needed for successful results.

A number of researchers have suggested the ways in which technologies could support autonomy. For example, Benson (2007) claimed that technologies might facilitate autonomy through their potential for widening learners' access to authentic material, allowing self-diagnosis, and providing forums collaborative learning outside of the class. Meanwhile, he cautioned that technology has a capacity to restrict freedom when it is used with technologies built in ways that reduce student agency and promote passive consumption. The ability for technology to be used in either way underscores how critical it is for teachers to purposefully build lessons that put students at the center rather than use automation as a means to provide instruction without them.

2.4. Research Gap

Although there is a rich body of works within two literatures (i.e., one focused on learner autonomy, the other focused on AI in education), less research exists at the intersection of the two topics. Moreover, when researchers do study this in-

tersection, they often treat AI tools primarily as ways to streamline instruction or deliver instructional materials; that is, they focus more on what the tools accomplish (efficiency) than on what students might become because of them (agencies). There has been little systematic research into whether and how the use of such AI tools may result in lasting shifts in learners' autonomous practices: such as goal setting, method choice, monitoring and motivation control. Moreover, most studies are based on transient interventions (or one-method design), lacking sufficient knowledge about how students really use such technologies to learn on their own. To fill this gap, the study takes a mixed-methods design in examining the impact of an artificial intelligence-assisted 16-week college English course on students' independent learning capability.

3. Theoretical Framework

The present research rests on two complimentary sets of theories, namely Zimmerman's (2002) self-regulated learning theory, and the concept of learner autonomy that has been developed within the field of applied linguistics. Together, these views form an overall window to understand how artificial intelligence tools might help in supporting self-directed language learning.

According to the self-regulated learning theory, students who are able to regulate their own cognitive, motivational, and behavioral processes will have greater success in education compared to those who do not (Zimmerman, 2002). Zimmerman described self-regulated learning process as consisting of three phases occurring periodically: planning, performance management and reflection. Initially students analyze the task, set goals, and plan how to do it. During task execution, they employ these techniques, monitor themselves, and adjust accordingly. Finally, they reflect on their performance, think about why things went so well (or badly) and then apply them in subsequent learning. Such a cyclic process is suitable for the current investigation as it captures concrete, measurable behaviors which are amenable to instruction.

Learner autonomy, as constructed by Benson (2011) and Little (1991), complements self-regulated learning theory in its focus on the socially and contextually situated aspects of autonomous learning. While self-regulated learning is mainly about one person's thinking and feeling process, learner autonomy is a broader concept of self-direction in study within certain social and institutional contexts, including negotiation of goals, planning carefully what resources and strategies to use, reflecting on whether one's approach is effective for learning. By combining these two views it becomes possible in this study to consider both aspects of self-regulation (the micro level) and the development of learner agency as a whole (the macro level).

Based upon this theory background, in this paper I present a self-regulated AI-assisted learning framework which views artificial intelligence technologies as supports to each of the three stages of SRL. At the pre-planning phase, AI systems may assist students in identifying what they currently know; where they need improvement; and what are realistic objectives for themselves. At the performance-

control phase, AI systems could provide personalized exercises with immediate feedback and suggestions on methods so that users see how the method changes while solving problems. In meta-cognition, the analytics generated by an AI system could demonstrate a student's trajectory of learning, identify patterns or commonalities within that learning, and enable the user to make decisions regarding subsequent content to be learned. In particular, the role of AI is more like a scaffolding structure which will disappear when students can control themselves better, instead of acting as an everlasting crutch replacing student's own power to act autonomously.

4. Methodology

4.1. Research Design

This study employed a convergent parallel mixed-methods design where numeric and descriptive data are collected simultaneously and merged together for developing comprehensive understanding about the studied phenomena (Creswell & Plano Clark, 2017). A one-group pre-test and post-test design was applied in its quantitative part to investigate the change of reported autonomous learning behaviours after receiving an instruction with embedded AI technologies. Note that such a design does not have a dedicated control group, so causal conclusions regarding AI's effect could not be made. The qualitative stage consisted of semi-structured interviews probing into the students' experience with, views toward, and use of AI tools for self-directed learning. Combining these two data sources enabled this research to triangulate its quantitative results against qualitative evidence, giving us a much more complete and nuanced account of what is going on here.

4.2. Participants

The study involved 126 first-year undergraduates who were not English majors and were taking a college English course at a finance- and economics-focused university in southwestern China. Of these students, 68 were women and 58 were men, and their ages fell between 18 and 21. All were in their initial year of university, and their English ability varied, as reflected in their scores on the college entrance examination. All students enrolled in the course were invited to participate voluntarily; all 126 participants completed both pre-test and post-test questionnaires and were included in paired-sample analyses. Every participant provided written informed consent. The university's research ethics board authorized the study, and participants were told that their responses would remain anonymous and be used solely for research.

4.3. Instructional Intervention

The embedded AI college English course lasted for four months (i.e., 16 weeks). It aimed at embedding the use of AI in both classroom teaching and out-of-class learning activities. Two classes were offered, each lasting 90 minutes weekly. Dur-

ing a class, approximately half an hour of AI-assisted learning tasks and spent the other part on teaching by teachers, group discussion, and collaborative task. Three types of AI platforms were used: 1) a commercially available automated writing evaluation platform (iWrite) providing grammatical, lexical/rhetorical feedback; 2) a smart spoken English practice system (iTest) providing pronunciation scoring and role-play conversation training; 3) an LLM-based tutoring agent for question-driven explanation and individualized exercises creation. I divided the usage of this agent in compulsory and optional parts. The students who had weekly compulsory AI assignment were recorded using the built-in platform back-end functionality for tracking completion; voluntary, off-classroom interaction with the AI learning assistant was encouraged; usage rate: reported by students in their learning journal (access to the full set of logs from the platforms during all voluntary student sessions were not available for ethical reason).

The course structure was based on the AI-supported individualized active learning model described in the conceptual framework, and at the beginning of the semester, students reflected on their own English language proficiency and studying habits, and based on AI-generated diagnostic reports set personal goals for what they wanted to improve during the term. During the term, students had to do weekly AI-assisted practice exercises, and kept a diary where they recorded their experiences of the learning process, assessed whether or not they were effective, and designed the changes. The teacher often instructed learners on how to wisely apply AI tools, such as verifying that machine-assigned ratings are accurate, or not over-relying solely on automatic suggestions.

4.4. Instruments

The quantitative data were collected by means of the Autonomous English Learning Questionnaire. The questionnaire, which is a self-report measure, consisted of items derived and adapted from various other validated self-regulated-learning questionnaires developed for foreign language learning contexts. Before administering it, the revised instrument underwent content validity check from two applied-linguistics scholars; a pilot test (with 42 comparable undergrads) was administered for fine-tuning the wording of items. The total scale yielded a Cronbach's alpha value of 0.86 in the pilot. In the full study, the coefficient was 0.87 before test and 0.89 after test that indicated enough consistencies between the items in this sample. There were a total number of 28 items in the questionnaire which were divided into four sub-scales including goal-setting and planning (7 items), strategy use (8 items), self-monitoring and evaluation (7 items) as well as motivational regulation (with 6 items). The response format for all statements was a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). This survey was administered at the beginning of the semester as a pre-test, and again at the end of the semester as a post-test. Internal consistency of this survey is an internal consistency (measured by Cronbach's alpha) of 0.87 at pretest and 0.89 at post-test, which is considered to be adequate.

We collected qualitative data through semi-structured interviews of 12 individuals who were purposefully sampled by maximum-variation sampling, stratified over the following two dimensions: their reported level of English-language fluency (low-, intermediate-, high-level, based on entrance-examination scores plus pre-test questionnaire results) and self-reported degree of AI-tool engagement (low, medium, high, drawn from learning-journal records of voluntary AI usage). The interview protocol explored students' perceptions of the AI tools, their usage patterns in- and out-of-class, the perceived influence on their learning behavior and motivation, as well as any problems or concerns they had experienced. The interviews were conducted individually with a duration of around 30-40 minutes. Each was carried out in Mandarin Chinese, and was audio-recorded (with permission of the participants).

4.5. Data Analysis

Numerical data were examined using descriptive statistics and paired *t*-tests to test for difference in pre-test vs post-test scores for the entire questionnaire, and all of the questionnaire's sub-scales. Cohen's *d* was calculated from within group pre-post change as a measure of effect size. The originally reported overall effect size ($d = 0.93$) was calculated using the pooled SD of pre- and post-test scores, while applying the pre-test standard deviation gives us a value of 0.88. We will make this difference explicit. All statistical analyses have been performed in SPSS v. 26.0, where significance is defined by $p < 0.05$.

Qualitative interviews were transcribed verbatim, and thematically analyzed according to Braun and Clarke's (2006) six-phase approach: getting familiar with the data, developing initial codes, determining possible themes, evaluating the themes, naming and defining the themes, and documenting results. Two researchers coded for inter-coder agreement 30% of transcripts and discrepancies were addressed via consensus discussion. During the convergent mixed-methods integration step, we compared our quantitative group-level change results to our qualitative numerical thematic findings; we paid particular attention both to areas where they converged and also hypothesized areas of divergence. For this data set, qualitative themes were broadly congruent with questionnaire trends and we did not find any major contradictory qualitative evidence that contradicted our quantitative pre- and post-intervention improvement. Qualitative themes shed light on possible mechanisms underlying changes in our quantitative findings, rather than separately establishing causality. The qualitative study was used to determine if there were consistent trends among students' experience, as well as to build an extensive, the contextualized interpretation of the way in which they perceived that the AI tool had impacted on their self-directed study.

5. Results

5.1. Quantitative Findings

Paired *t*-test analyses showed that students' self-directed learning behaviors im-

proved significantly between the pre-test and post-test. **Table 1** reports the means, standard deviations, *t* statistics, and effect sizes for the full questionnaire and each of its sub-scales.

Table 1. Pre-test and Post-test comparisons of autonomous learning behaviors.

Sub-scale	Pre-test M (SD)	Post-test M (SD)	<i>t</i>	<i>p</i>	<i>d</i> ₁ (pooled)	<i>d</i> ₂ (<i>d</i> _z)
Goal-setting and planning	3.12 (0.68)	3.68 (0.61)	8.76	<0.001	0.87	0.78
Strategy use	3.25 (0.72)	3.79 (0.65)	7.93	<0.001	0.79	0.71
Self-monitoring and evaluation	2.98 (0.75)	3.56 (0.69)	8.21	<0.001	0.81	0.73
Motivational regulation	3.05 (0.70)	3.61 (0.64)	8.45	<0.001	0.84	0.75
Overall autonomous learning	3.10 (0.63)	3.66 (0.58)	9.87	<0.001	0.93	0.88

Two effect-size values are provided. *d*₁ uses pooled pre-post standard deviation; *d*₂ uses pre-test standard deviation.

As shown in **Table 1**, there was an increase from pre-test to post-test on the overall autonomous learning scores (from 3.10 to 3.66; significant). The overall effect is *d*₁ = 0.93 with the pooled standard-deviation definition of *d*₁ and *d*₂ = 0.88 with the paired-samples definition $d_z = t/\sqrt{N}$, consistent with what would be predicted from *t* = 9.87 on a sample of size *N* = 126. The same was true for all four sub-scales: they too showed statistically significant gains between pre- and post-tests. We cannot conclude that this result can be attributed to the presence of an artificial intelligence in our experiment due to experimental limitations.

5.2. Qualitative Findings

Analyzing the interviews revealed four key themes describing students' experiences using AI tools and their views on the tools' influence on independent learning.

Theme 1: An accessible and patient tutor. Many students characterized the AI tools as providing levels of accessibility and patience not possible for humans to provide within a large enrollment class. Students reported being able to ask the AI learning assistant questions anytime, repeat practice problems over and over again, get instant feedback, and not feel criticized or ashamed. As one student said, "Previously I would not ask the teacher a question if I felt like my question is too basic, but with the AI buddy you could ask any question and it doesn't get annoyed so it makes you feel comfortable enough to attempt problems yourself". This perceived ease-of-use seemed to reduce some of the psychological barriers that exist between many students and self-directed study, thus giving them more responsibility, autonomy, and incentive to act on their own behalf.

Theme 2: Instantaneous feedback, improved self-monitoring. Students frequently emphasized the benefit of instantaneous feedback from the automatic

writing grading system and speaking practice program. They described how instant feedback on their written and spoken output enabled them to identify mistakes and correct them as they happened rather than after a few days when they received a teacher's commentary. Some students also noted that explicit instruction caused them to be more aware of recurring errors in their work and more able to proofread their own work. One student put it this way, "The pen automatically shows me when there is a grammatical mistake that I have made, as well as telling me why it's incorrect. After some while, I began to notice those errors on my own before I even hand in my written work. I believe this has made me an autonomous learner". The above finding corroborates the quantitative finding of notable increase in the self-monitoring and evaluation sub-scale.

Theme 3: Personalized practice and greater motivation. Students liked how the AI systems could adapt the difficulty level of the practice problems depending on student performance. They stated that this personalized practice made learning interesting and more relevant for them, which also enhanced their desire to practice English after classes. A student mentioned: "The speaking system provides me with a topic at my level. If I answer correctly, it becomes difficult for me and if not then it helps me out. So I feel like doing this continuously as I can see my progress". Motivational regulation sub-scale has shown good improvement from the quantitative data, and these results are consistent with the qualitative evidence indicating personalized, adaptive practice as a key driver of this shift.

Theme 4: Critical use issues and possible dependency. Although students generally had a positive perception towards these AI tools in general, there were some concerns that students raised as well. A few students expressed their concern about equality of the AI-generated comments, finding that at times the software offered suggestions which were grammatically correct but stylistically inappropriate or did not grasp what was meant by meaning. Others agreed that using these AI tools was convenient and can result in reliance on them; one student even admitted that he/she had sometimes used the AI writing assistant to create whole sentences or paragraphs instead of using it as a feedback tool. One student observed, "It's tempting to have AI do all the writing, so I need to remind myself that I'm trying to develop my English skills, not simply earn a high grade on an assignment." The teacher's guidance on how to use these tools critically has been really important. This theme underscores the necessity of explicit instruction for critical AI literacy and intentional pedagogical safeguards to prevent dependency and preserve learner agency. Mixed-methods integration: Qualitative themes converged well with quantitative pre-post patterns. Interview accounts illustrated potential pathways (reduced anxiety, instant feedback, adaptive practice) whereby AI might support self-reported changes in goal-setting, self-monitoring and motivational regulation. No major contradictory qualitative evidence was identified that conflicted with questionnaire outcomes. Still, interview data represent subjective student perceptions and cannot independently prove AI caused the observed behavioral shifts.

6. Discussion

The results presented here demonstrate that following participation in a college English course integrated with AI tools, learners reported perceived gains on several aspects of their autonomous learning behaviors to a statistically significant level. However, we should note that because our research follows the one-group pre-post test approach, any conclusion regarding causality is not certain: maturation, course-wide non-AI learning activities, and Hawthorne effects might also be contributing to the observed changes, and we do not have evidence of whether or not students' reported change persists throughout a semester. The quantitative results show that there are large effect sizes for improvements in goal-setting, strategy use, self-monitoring and motivational regulation, whereas the qualitative results shed light on how the AI tool supports those changes.

The observed increase for setting goals and planning is understandable within the framework of Zimmerman's (2002) forethought phase of SRL: The generated diagnostics and assessment of proficiency gave the students an objective overview of where they stood, which assisted in setting more personalizable and realizable goals for learning. Many students indicated that prior to the programme their goals tended to be very general—such as “learn more English”—but they were able to identify what needs improvement and set concrete goals with specific metrics thanks to the AI evaluation systems. This result indicates that AI tools could help in the forethought process of goal-setting by eliminating some level of uncertainty which hinders L2 students' ability for strategic foresight.

The enhancement of the self-monitoring and evaluation process also fits with Butler's (2002) claim regarding how feedback contributes to the development of autonomy. Immediate, detailed feedback from the AI tools enabled students to find mistakes and monitor their improvement process in real-time, helping them understand assessment standards better so they could be better judges of themselves as well. The qualitative findings indicated that overtime, students started anticipating what kind of feedback they would get and correcting themselves before submitting an assignment, i.e., shifting regulation from outside into inside. Such slow internalization is a possible mechanism by which AI scaffolding could build autonomy.

The improvement in motivational regulation is consistent with Dickinson's (1995) finding that autonomy and motivation are closely related. The AI practice tools personalized the activity for each student and adapted it overtime, making study more engaging and allowing students to believe they were progressing and becoming proficient, thus increasing their intrinsic motivation for learning. The students stated that being able to work on problems at one's own speed with instant feedback meant they were more likely to spend time working independently on questions themselves. This result indicates that AI systems could be used as a means of supporting motivational control through facilitating ideal levels of challenge and offering regular, constructive comments which keep you interested in the game for long periods of time.

Still, there are some issues identified by these qualitative results which should not go unaddressed when incorporating AI into language pedagogy: reliance on AI tools and imperfections with AI-generated comments call attention to a need for clear teaching about critical AI literacy. Students require guidance in evaluating AI outputs, treating AI as an assistant but not a substitute for thinking on its own, and staying actively accountable for their learning. This study incorporated support through frequent teacher-facilitated conversations regarding the limitations of AI and thoughtful ways to deploy it, and qualitative results suggest that learners valued such instruction. Such results align with Kasneci et al.'s (2023) warning that pedagogical utility from large LLMs depends critically, purposeful use rather than uncritical adoption.

There are some caveats. First of all, this study is a before-and-after assessment for one group only, i.e., there is no control group, so it is not possible to conclude that any benefits were due solely to the AI intervention. There are many other confounding effects including simply a student's natural development in their first year at university and the Hawthorne effect of being observed may have caused the change. Future work would do well to use randomized control designs in order to be more confident about causal links. Furthermore, because the study was conducted within one university, involving fairly homogeneous cohort of incoming freshman non-English major students, its results might not generalize all the elements. Third, the length of time for this experiment is only one semester; it is uncertain if there is any lasting change to students' autonomous learning behavior after a longer term. Finally, the quantitative component of this work relied on self-reported questionnaire results from students that may have been subject to reporting bias. Future research can augment such reports with independent measures of individualized learning, e.g., use analytics gathered from AI applications.

7. Conclusion and Implications

This study examined correlations between a college-English, AI-infused course and student's self-reported autonomous-learning ability. The mixed methods results suggest that thoughtfully designed AI infusion is associated with statistically-significant increases in self-reported improvement on goal setting, strategy use, self-monitoring, and motivational regulation. Due to the limitations of the study design we are unable to make causal claims or make any claims about longer term durable autonomy. Our qualitative analysis found that AI tools were acting as an accessible tutor, immediate feedback providers, and adaptive practice partners in order to reduce psychological barriers to self-directed learning and facilitate incremental internalization of regulation processes. Meanwhile, the research uncovered the need for critical AI literacy education in order to avoid over-reliance, ensuring that AI tools are used not as replacements for learner agency but instead as scaffolds toward it.

The findings imply some pedagogical implications for the university level English classes. Firstly, teachers need to proactively integrate artificial intelligence ap-

plications in curriculum design, tying their use to clear learner-autonomy goals rather than treating them as optional supplements. Secondly, teachers need to give explicit guidance about important AI use, helping students build the capacity to assess AI outputs as well as appropriately utilize tools; Thirdly, instruction should be designed with built-in opportunities for reflection and self-assessment, such as learning logs or self-evaluations in order for learners to internalize these regulatory processes which are at first supported by an AI tool. Fourthly, curriculum developers will want to explore ways in which artificial intelligence might support differentiated instruction, scaffolded content, and curricular delivery tailored for each learner's current level of understanding.

The study also has implications for educational research. Future research should use more robust methods, such as comparison groups and long-term follow-ups, to determine whether AI-assisted autonomy development produces causal effects and whether those effects endure. Researchers should additionally investigate whether learner characteristics—including existing levels of autonomy, digital competence, and motivational dispositions—influence how effective AI-based interventions are. Further studies should create and empirically validate pedagogical models for incorporating AI tools into language programs in a structured way, with the specific aim of strengthening learner autonomy.

To sum up, AI can provide great promise to promote the development of students' autonomy learning in College English teaching, but harnessing it calls for pedagogical scaffolding which places the use of AI at the service of autonomous learning and not the other way around. Given the rapid development of artificial intelligence, language teachers are urged to be mindful and judicious about how such tools can be used so as not to compromise this primary pedagogical aim for cultivating competent, self-driven lifelong students.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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