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Article

Artificial Intelligence and Personalized English Learning Plan: A Survey Study Based on Applied Undergraduate Programs

Yi Wang [1] and Chaofeng Hou [2]*

[1] School of Foreign Languages and Cultures, Geely University, Sichuan, China
[2] School of Economics, Sichuan University, Sichuan, China

Correspondence: Chaofeng Hou, School of Economics, Sichuan University, Sichuan, China
Email: 18708987403@163.com

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Abstract: Against the backdrop of the deep integration of artificial intelligence (AI) technology and the field of education, as well as the gradual popularization of cross-campus teaching models, personalized English learning has become a key approach to enhance students' learning efficiency. Based on core learning motivation theories such as Self-determination theory and Achievement Motivation theory, this study, which takes 192 students from Geely University as the research sample, systematically analyzes the current status, motivation characteristics, and path dilemmas of college students using AI tools for English learning in the cross-campus environment. These findings show that the study in this paper can, to some extent, recommend the most effective AI-empowered personalized English learning plan that adapts to cross-campus teaching scenarios, and provide practical reference and decision-making base for English teaching reform in colleges and universities in China.

Keywords: Learning Motivation Theory; Cross-Line Campus; AI; Personalized English Learning Plan

1. Introduction

With the iterative upgrade of artificial intelligence (AI) technology and the accelerated promotion of digital transformation in education, a cross-campus model that integrates online independent learning with offline classroom teaching has become the mainstream of higher education (Hwang et al., 2020). As a subject that combines both practical and humanistic attributes, English learning has an inherent compatibility with the characteristics of AI technology, particularly in terms of its demand for personalization and real-time feedback (Luckin et al., 2016). Application-oriented universities represented by Geely University of China offer a variety of subjects, spanning literature, science, engineering, and arts. Moreover, most students have not yet passed the College English Test Band 4 (CET-4), demonstrating diverse and differentiated English learning needs.

Self-Determination Theory (SDT), proposed by American psychologists Deci E. L. and Ryan R. M., emphasizes that autonomy, competence, and relatedness are three core psychological needs that stimulate individuals' intrinsic motivation (Deci & Ryan, 2000). AI tools, through personalized content recommendations and real-time feedback mechanisms, can effectively support students' autonomous learning and the development of competence; meanwhile, interactions and connections between teachers and students in cross-line scenarios help to strengthen their sense of relatedness, thereby collaboratively enhancing learning motivation (Ryan & Deci, 2020). Achievement Motivation Theory, developed by Harvard psychologists David C. McClelland and J. W. Atkinson, divides individuals' achievement motivation into two typical tendencies: "pursuing success" and "avoiding failure" (McClelland, 1985). In the process of English learning, students' use of AI tools to improve test scores or complete academic tasks can be viewed from a motivational perspective as goal-directed behavior driven by achievement motivation (Elliot & McGregor, 2001). The Self-Regulated Learning Theory, proposed by American educational psychologist Zimmerman B. J., emphasizes that learning is a cyclical process in which learners actively set goals, monitor the process, and dynamically adjust strategies (Zimmerman, 2002). In cross-line campus environments, AI tools can continuously track and record the learning process, effectively complementing teacher supervision and guidance, jointly helping students achieve self-regulation of their learning behaviors (Panadero et al., 2016). Against this backdrop, exploring the application logic of AI in cross-campus English learning and analyzing the underlying motivational mechanisms of student behavior through learning motivation theory is extremely significant for constructing efficient and personalized learning plans.

2. Methodological Design for Investigating College Students' English Learning Motivation in AI-Enhanced Cross-Campus Settings

2.1 Survey Participants and Samples

Adopting a random sampling method, this survey targeted undergraduate students at Geely University, and a total of 192 valid questionnaires were retrieved. The sample covered students from liberal arts (23.96%), science (20.83%), engineering (30.21%), fine arts (23.96%), and other majors (1.04%), demonstrating good representativeness. Besides, 81.25% of the participants have not passed the College English Test Band 4 (CET-4), which accurately reflects the typical learning situation of students in application-oriented colleges who have weak English foundations and an urgent need for improvement.

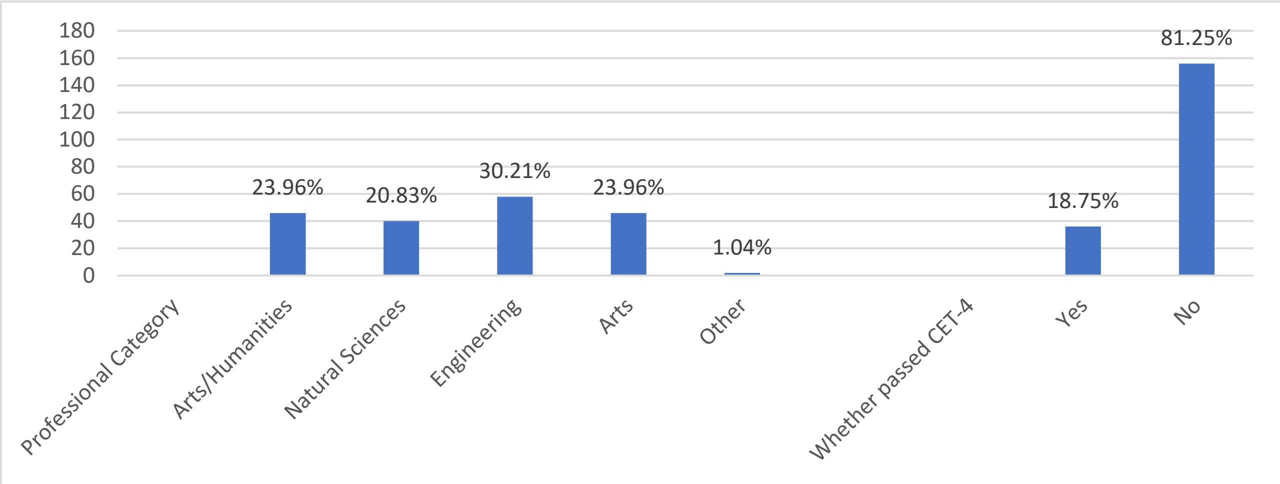

Figure 1. Data distribution by Major Category and Whether CET-4 is Passed

2.2 Survey Instruments and Methods

This study applied a mixed research design that primarily focuses on quantitative research supplemented by qualitative analysis (Creswell & Plano Clark, 2017). A systematic survey was conducted among undergraduate students at Geely College through an online questionnaire platform. The survey instrument was a self-developed “Questionnaire on College Students’ Use of AI Tools for Learning English”, which was designed with reference to relevant theoretical frameworks on educational technology acceptance and language learning strategies (Davis, 1989; Oxford, 2016), ensuring the content validity of the measurement tool.

The questionnaire covers four major dimensions. In the basic information section, demographic data such as students’ major and English proficiency were collected; in the core survey module, the survey deeply examined the frequency distribution of students’ use of AI tools, their type preferences, purposes of use, and their application across different English skill areas through various formats including single-choice questions, multiple-choice questions, and matrix scale questions; in terms of learning motivation and perceived effectiveness, a five-point Likert scale was used to measure students’ agreement with the advantages and disadvantages of AI-assisted learning; at the level of academic performance assessment, a learning outcome evaluation system was constructed by adopting indicators such as students’ self-reported English course grades and CET-4 passing status.

In terms of data collection and processing, this study strictly adhered to research ethics, and all participants completed anonymous questionnaires under the premise of informed consent, ensuring the reliability and confidentiality of the data. For the collected quantitative data, we used SPSS statistical software to conduct systematic descriptive statistics and cross-tabulation analyses; simultaneously, we performed detailed content analysis on the responses to open-ended questions in the questionnaire (Krippendorff, 2018) to gain deeper insights into students’ experiences and needs. This multi-method and multi-perspective research strategy provides a solid methodological foundation for comprehensively understanding the characteristics of college students’ English learning in an AI-enhanced environment.

3. Analysis of Survey Results on AI-Enhanced English Learning in Cross-Campus Settings

According to the analysis of the questionnaire data, students’ learning motivation exhibits a clear achievement-oriented characteristic. In terms of learning objectives, the four options “improving exam scores” (25.52%), “broadening knowledge” (23.44%), “enhancing practical application ability” (22.4%), and “completing assignments/papers” (21.88%) show a balanced distribution, collectively forming a dual-driven pattern of “exam performance + application.” This fully reflects the goal-oriented characteristic of “pursuing success” in achievement motivation theory (Pintrich, 2003).

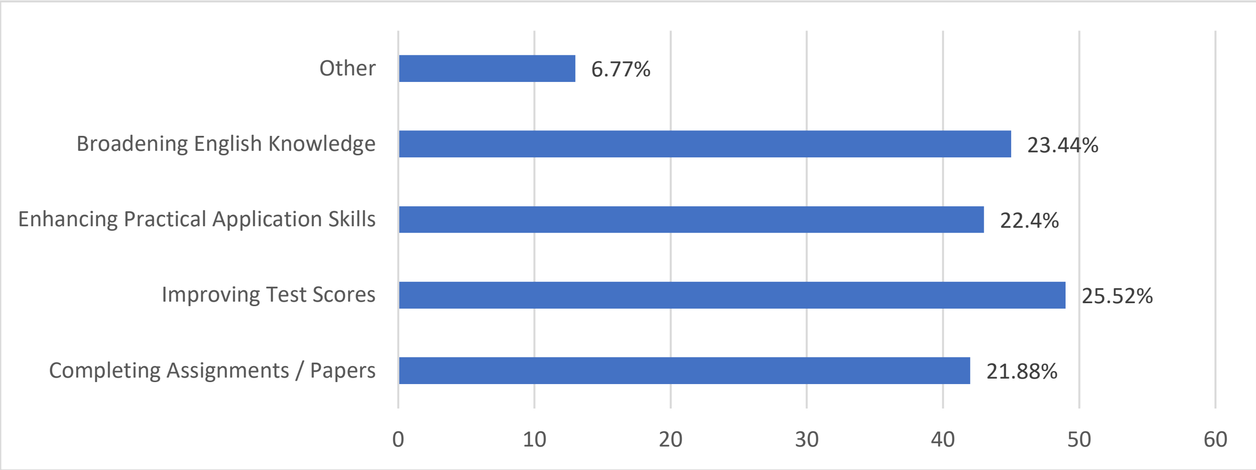

Figure 2. Usage Purpose Distribution

In terms of AI tool usage frequency, 52.08% of students use them "occasionally" (1-3 times per month), 25.52% use them "regularly" (1-3 times per week), and only 8.85% use them "frequently" (more than 4 times per week). Notably, only 13.54% of students reported never having used AI tools to assist with English learning. These data indicate that although AI tools have become an auxiliary means for most students in English learning, their usage patterns are still primarily low-frequency and supplementary. The habit of frequent, in-depth use has not yet formed, and the potential of AI tools in English learning remains to be further explored.

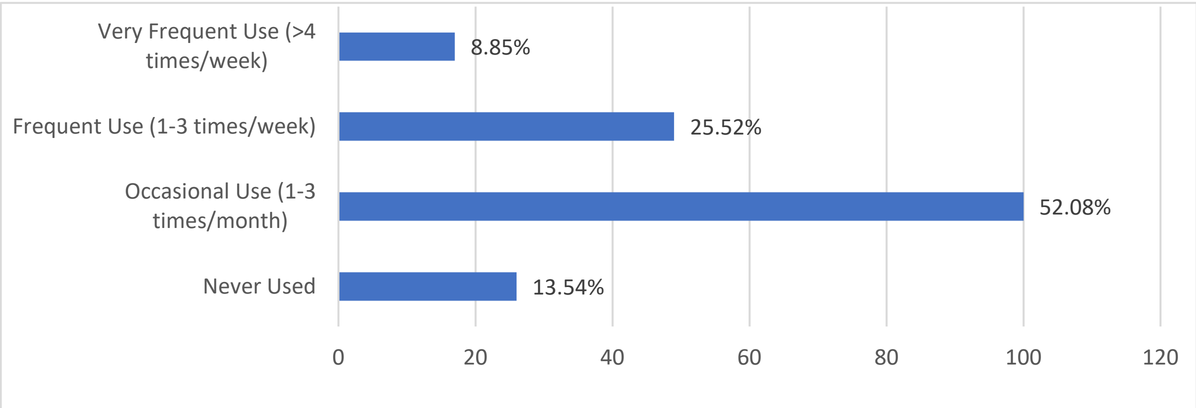

Figure 3. Using Frequency Distribution Figure

According to survey data, students show a clear tendency to concentrate on specific AI tools. General-purpose AI tools dominate the market, with the usage rates of ChatGPT, DeepSeek, and Doubao reaching as high as 76.04%. Among specialized tools, the AI versions of Baicizhan (34.9%) and Youdao Dictionary (25.52%) have relatively high usage rates, while oral-focused tools such as Liulishuo AI Coach have significantly lower usage rates (10.42%). This preference for certain tools closely aligns with how students allocate their time in English learning-vocabulary and grammar study occupies the largest proportion (22.14%), indicating a significant correlation between students' choice of tools and their fundamental learning needs.

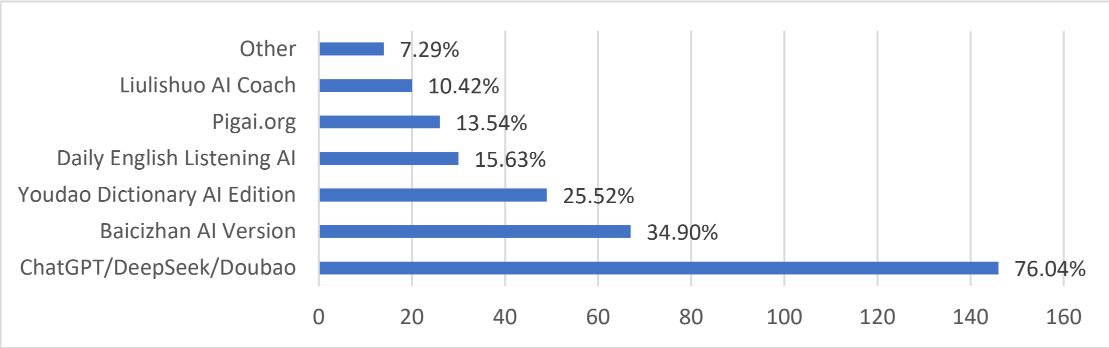

Figure 4. Distribution of AI Tools that have been used

3.1 AI-Assisted English Learning Content

Students' use of AI covers practicing skills such as listening, speaking, reading, writing, and translation with a tendency to focus more on input than output. Among the combined proportions of "frequently used" and "mainly relied on", "vocabulary memorization" (37.51%) and "reading comprehension" (31.25%) ranked highest, while the frequency of "oral expression" (26.05%) and "writing practice" (28.13%) was lower. This corresponds with the fact that "vocabulary and grammar learning" (22.14%) accounts for the largest proportion of students' weekly time allocation.

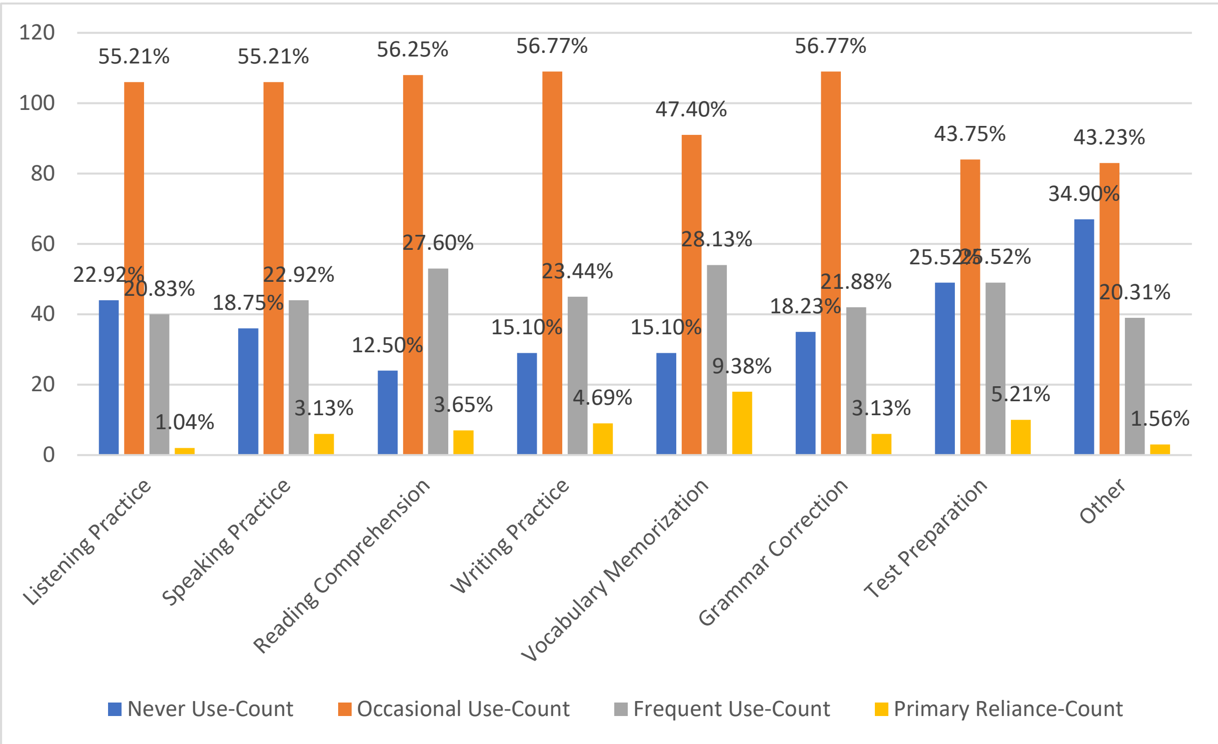

Figure 5. Application Scenarios and Dependency Levels for AI-assisted English Learning

In terms of the allocation of students' extracurricular English learning time, the greatest investment is in vocabulary and grammar study (22.14%) and reading practice (18.11%), while output-oriented activities such as speaking (14.95%) and writing (13.74%) receive relatively less time. This further indicates that the current learning pattern of students still leans toward traditional foundational knowledge accumulation, with AI tools primarily playing a role in enhancing efficiency rather than reshaping the learning model.

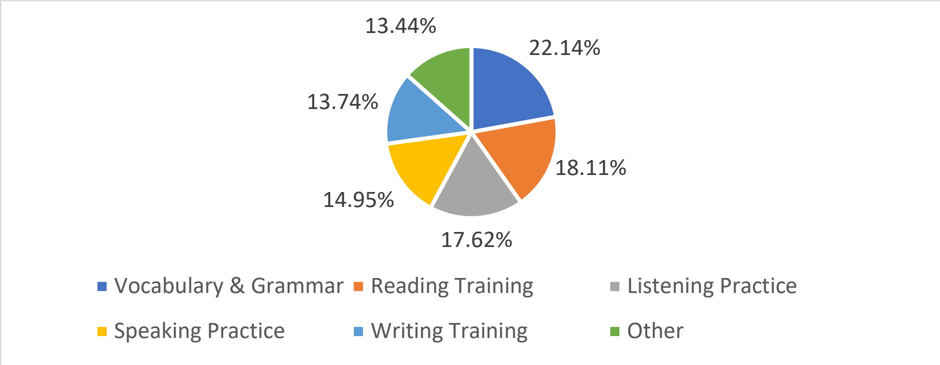

Figure 6. Time Investment in AI-assisted English Learning

3.2 Advantages and Drawbacks of AI-Assisted English Learning

The three major advantages accepted by students most are “rich and diverse resources” (average score 3.97), “accessible anytime and anywhere” (average score 3.94), and “instant feedback and correction” (average score 3.74). These precisely address the core needs in cross-campus learning for convenient access to resources, flexible learning time and space, and timely process feedback, fully satisfying the “autonomy” and “competence” in self-determination theory (Deci & Ryan, 2000).

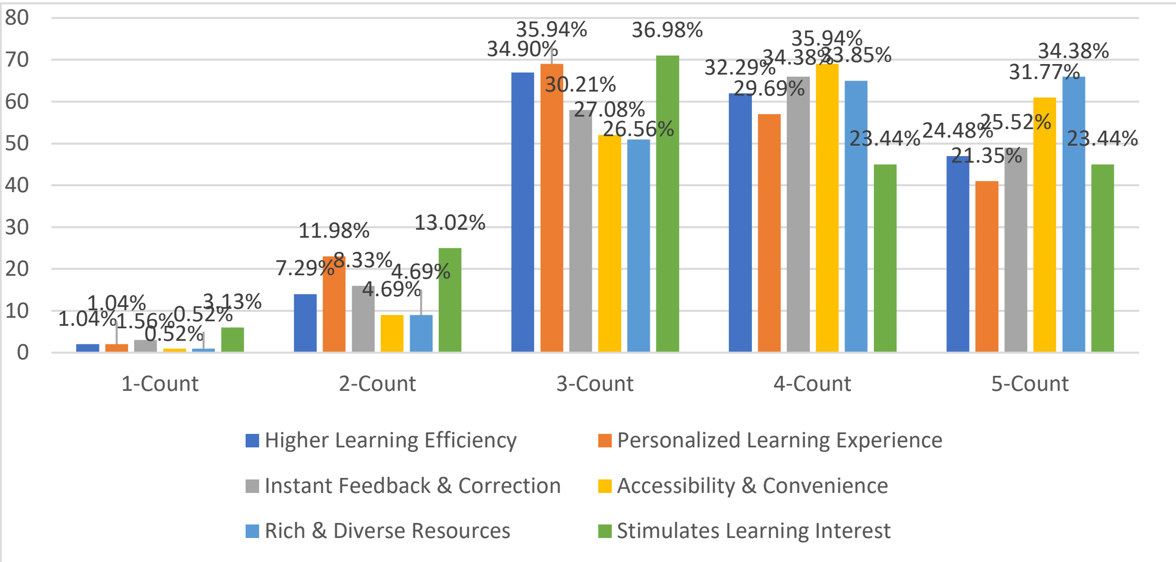

Figure 7. Advantage Evaluation Scale Bar

The main challenges are reflected in “requiring strong self-discipline” (average score 3.53) and “lack of genuine interpersonal interaction” (average score 3.16). The former reveals that students’ self-regulation abilities are challenged in an online environment without external supervision (Zimmerman, 2002); the latter points out the negative impact of purely AI-based interactions on the establishment of a “sense of belonging” (Ryan & Deci, 2020). In addition, “feedback content may be inaccurate” (average score 3.1) is also an important factor limiting students’ use of AI in depth.

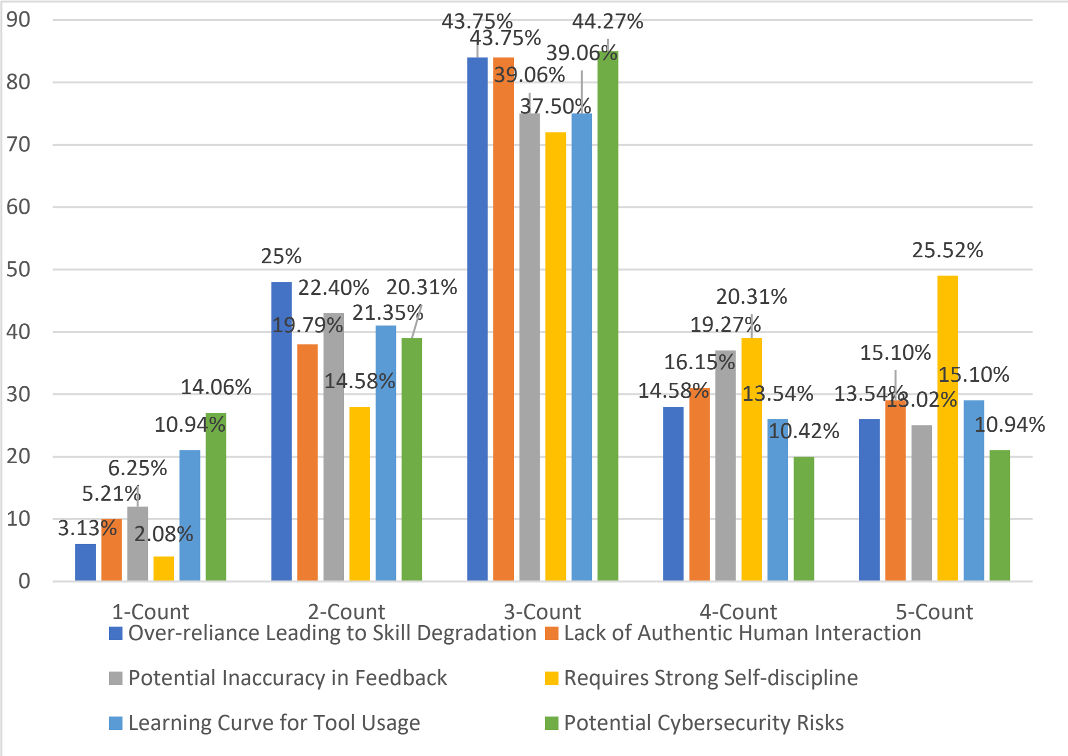

Figure 8. Disadvantage Evaluation Scale Bar

3.3 The Role of English Teachers in the AI Era

The survey data clearly indicates students' expectations of teachers in the new era. As many as 71.35% of students hope that teachers can provide "formulation and guidance of personalized learning plans", 65.1% of students need teachers to "design and guide effective language output exercises"; more than half of the students also selected "guidance and supervision during the learning process" (58.85%) and "tutoring and answering questions after autonomous learning" (55.21%). This suggests that students hope their English teacher could shift from traditional knowledge transmitters to designers of learning paths, supervisors of the learning process, stimulators of higher-order thinking, and coordinators of human-computer collaboration (Hattie, 2012).

Figure 9. English Teachers' Role Expectations in an AI-Assisted Environment

4. 4. The Actual Problems Existing in Designing Personalized English Learning Plan

4.1 Uneven Motivation Stimulation

Although the personalized experience of AI tools (average score 3.58) and the diversity of resources (average score 3.97) have somewhat stimulated learning interest, the recognition of "stimulating learning interest" is the lowest among the advantage dimensions (average score 3.51). Most students' usage behavior remains driven by external motivations such as "completing assignments/papers" (21.88%) and "improving exam performance” (25.52%), while intrinsic motivations based on curiosity and self-improvement have not been fully activated, resulting in a relatively low frequency of use (frequent use accounts for only 8.85%).

4.2 Low Integration in Cross-line Scenarios

There is a “disconnect: between online AI learning and offline classrooms. On one hand, students mainly use AI tools for basic training such as vocabulary memorization (28.13% use frequently) and reading comprehension (27.6% use frequently); on the other hand, teacher guidance in offline classrooms has not effectively connected with online learning data. 71.35% of students hope that teachers can provide “personalized learning planning and guidance”, reflecting insufficient coordination in path planning across online and offline scenarios.

4.3 Limitations in the Use of AI Tools

Although general-purpose AI tools have a high usage rate (76.04%), most students only use them for basic Q&A and vocabulary lookup, while in-depth features such as speaking practice and writing correction are used less frequently. This contrasts with the demand for “speaking expression” (55.21% occasionally use) and “writing training” (56.77% occasionally use). 39.27% of students believe that AI feedback “may be inaccurate: (average score 3.1), and this lack of trust makes it difficult for students to treat AI as a core learning partner, limiting the effectiveness of personalized error correction and strategy optimization functions.

4.4 Lack of a Support System

The self-regulation theory emphasizes a “monitor-feedback-adjust” closed loop, yet the current support system has a dual gap, which is there is a lack of dynamic tracking of learning behaviors and personalized reminders without teacher’s guidance; while on teacher’s side, AI data cannot be used for targeted tutoring timely. 55.21% of students need “tutoring and Q&A after autonomous learning”, and 58.85% need “guidance and supervision during the learning process”, reflecting insufficient external support to sustain motivation.

5. Designing Personalized English Learning Plans in the AI Era

Based on the aforementioned challenges and integrating core perspectives such as self-determination theory and achievement motivation theory, a four-dimensional cross-disciplinary personalized AI English learning plan for campuses is constructed, consisting of “motivation stimulation - plan implementation - feedback optimization - support assurance”.

5.1 Motivation Stimulation

In the dimension of motivation activation, a dual-drive mechanism combining "intrinsic + extrinsic" motivation should be constructed. On one hand, intrinsic motivation should be fostered based on Self-Determination Theory. First, through autonomy empowerment, students are allowed to select combinations of AI tools according to their major characteristics (e.g., engineering students focus on AI resources for technical English, while art students prioritize AI materials for intercultural communication), and set their own learning goals and learning plans independently, thereby strengthening their sense of ownership in learning (Reeve, 2012). Second, competence should be enhanced with the help of AI tools-AI can push progressive tasks based on students’ initial proficiency levels and provide real-time feedback such as grammar error correction and oral English scoring, enabling students to clearly perceive their own progress and further improve their sense of learning achievement (Deci & Ryan, 2000). Third, a sense of belonging should be built by integrating AI online practice with offline group activities; for instance, AI is used to generate oral English topics, followed by offline group discussions to make up for the shortage of interpersonal interaction in AI-assisted learning. On the other hand, extrinsic motivation should be guided based on Achievement Motivation Theory. First, goal visualization should be achieved-AI tools generate learning progress reports such as vocabulary mastery rates and writing score improvement curves, which are linked to CET-4/6 exams and professional English needs to help students clarify the value of learning (Pintrich, 2003). Second, incentive mechanisms should be designed, and teachers can select “Weekly Progress Stars” based on AI data and incorporate the duration and quality of AI-assisted learning into regular grades, so as to strengthen students' goal-oriented behaviors (Elliot & McGregor, 2001).

5.2 Plan Implementation

In the dimension of plan implementation, an online-offline collaborative model "AI empowerment online + teacher leadership offline" should be formed. The online AI-powered personalized learning module is structured in three layers. At the basic layer, AI-enhanced versions of Baicizhan (a vocabulary-learning app) and Youdao Dictionary serve as the core to establish a daily training system for vocabulary and grammar, with AI pushing review tasks to students based on the forgetting curve. At the competence layer, general AI tools such as ChatGPT should be applied for simulated oral English conversations and first-draft writing generation, while accurate error correction is provided in combination with Pigaiwang (an English writing correction platform). At the expansion layer, AI from Daily English Listening pushes professional-related listening materials; AI automatically marks difficult points in the materials and generates extended reading links to meet students' needs for knowledge expansion. The offline teacher-led personalized guidance module proceeds from three aspects. First, plan customization, which means teachers rely on data generated by the AI platform, e.g., students' high-frequency error types, weak competence areas to formulate monthly personalized learning paths for each student, such as "vocabulary consolidation + writing improvement" and "listening breakthrough + oral English enhancement". Second, in-depth tutoring-teachers conduct offline thematic courses to address complex issues that AI cannot solve, e.g., long and difficult sentence analysis, cultural background interpretation, and provide one-on-one Q&A sessions based on students' AI learning records. Third, output training-teachers design offline output tasks, e.g., English speeches, academic paper writing according to students' writing and oral English weaknesses identified by AI, helping students improve their practical English application abilities.

5.3 Feedback Optimization

In the dimension of feedback optimization, a dual-track mechanism combining "AI intelligent feedback + teacher professional feedback" should be established. On one hand, the precision upgrading of AI feedback should be promoted. First, hierarchical feedback should be implemented and for basic errors such as spelling and grammar, AI provides immediate correction and example sentences for reference; for complex issues like logical structure and pragmatic appropriateness, AI marks the first and then pushes them to the teacher terminal, waiting for teachers to provide professional feedback. Second, trust should be emphasized - Credibility is indicated in AI feedback content, such as labeling "95% credibility for grammar error correction"; meanwhile, AI models should be continuously trained through feedback cases verified by teachers to gradually improve the accuracy of AI feedback. On the other hand, the personalized implementation of teacher feedback should be advanced, too. First, data-driven feedback should be carried out - teachers check the class-wide common problem reports and students' individual difference reports generated by AI every week, organize centralized explanations for high-frequency errors shown in the reports, and provide offline tutoring for students' personalized problems (Hattie, 2012). Second, process-oriented feedback should be implemented - teachers track students' task completion through AI tools; if students show behaviors such as procrastination and perfunctoriness, teachers give timely reminders; if students make significant progress, teachers provide targeted recognition, so as to strengthen the maintenance of students' learning motivation (Zimmerman & Schunk, 2011).

5.4 Support Assurance

In the dimension of support and guarantee, a trinity system of "tools-teachers-systems" should be built. First, tool support should be strengthened. AI English learning tools certified by educational authorities are screened and introduced, and free access rights should be provided to students in order to lower the threshold for tool acquisition; meanwhile, "practical training on AI English learning tools" should also be regularly carried out, and through methods such as case demonstrations and hands-on exercises, students and teachers could operate tool proficiently, reducing usage barriers. Second, teacher support should be optimized. on the one hand, special training on teachers' AI skills should be enhanced, focusing on improving teachers' ability to formulate differentiated teaching strategies using AI data; on the other hand, "AI + teacher" collaborative lesson preparation mechanism should be established, guiding teachers to integrate teaching resources generated by AI, e.g., personalized exercises, extended materials into offline lesson plan design, realizing in-depth integration of technology and teaching. Third, system support should be improved. Management Norms for AI English Learning in Cross-Campus Settings should be formulated, clarifying boundary contents such as the scope of AI tool usage and data privacy protection requirements to avoid abuse or misuse; at the same time, a scientific learning effect evaluation system is necessary too, which combines students' AI learning data, e.g., tool usage duration, task completion quality with offline performance, e.g., classroom participation, exam scores for comprehensive evaluation, ensuring the comprehensiveness and objectivity of the evaluation.

6. Conclusion

Research data from Geely University shows that AI tools are currently widely applied in college students' English learning process, but still there are several issues such as oversimplified usage levels, insufficient integration between online and offline learning phases, and limited effectiveness in stimulating learning motivation. By designing a personalized AI English learning plan on campus based on learning motivation theory, this paper proposes a systematic integration of the four dimensions of "motivation stimulation - path implementation - feedback optimization - support assurance", which can achieve an organic combination of online AI assistance and offline teacher guidance effectively, better meet students' personalized learning needs, and enhance the durability and stability of learning motivation.

Future research can be further deepened in the following areas. First, expand the sample coverage to conduct an in-depth analysis of the personalized learning characteristics and differences in needs among students with different professional backgrounds and varying levels of English proficiency; second, keep pace with the development of artificial intelligence technology, focusing on exploring the implementation methods of generative AI in scenarios for cultivating advanced abilities such as English academic writing and cross-cultural communication (Luckin et al., 2016); third, conduct longitudinal tracking studies to systematically assess the actual impact of this learning pathway on students' overall English proficiency development and the maintenance of learning motivation (Creswell & Plano Clark, 2017), thereby providing more practical solutions for promoting the deep integration of cross-disciplinary campus education and AI technology.

DATA AVAILABILITY STATEMENT

All data generated or analyzed during this study are included in this article. The data that support the findings of this study are available from the corresponding author upon reasonable request.

AUTHOR CONTRIBUTIONS

Yi Wang: Conceptualization, Methodology, Data Collection, Formal Analysis, Investigation, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing.
Chaofeng Hou: Supervision, Project Administration, Writing – Review & Editing, Funding Acquisition.
All authors have read and approved the final version of the manuscript.

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