

How generative artificial intelligence empowers Generation Z college students' learning

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Abstract. To investigate the mechanisms through which Generative Artificial Intelligence (GenAI) empowers Generation Z college students' learning through human-AI collaboration, this study surveyed undergraduate and postgraduate students born between 1995 and 2009. A questionnaire was administered across four dimensions, including learning behaviors, awareness of the recommendation-based postgraduate admission policy, preferences for prospective postgraduate institutions, and the use of AI tools, yielding 300 valid responses. An empirical analysis was conducted using a combination of reliability and validity tests, correlation analysis, two-way analysis of variance, and multiple linear regression. The results show that the measurement scale demonstrates good reliability and validity. Students' use of GenAI remains largely at a superficial level, such as assisting with assignments, while the pursuit of recommendation-based postgraduate admission constitutes a core driver of digital learning. The four dimensions are significantly and positively correlated, and the sample exhibits pronounced group stratification. Academic ranking has a stable positive effect across different year levels, whereas year level itself has no independent effect. Awareness of the recommendation-based postgraduate admission policy, AI use, and postgraduate study planning positively predict learning behaviors, with policy awareness exerting the strongest predictive effect. Simply providing open access to AI tools may exacerbate academic stratification, while digital literacy does not develop spontaneously with students' progression through different year levels. Accordingly, this study proposes several reform pathways, including targeted and stratified education, deeper integration of AI driven by students' postgraduate admission needs, staged cultivation of digital literacy, and coordinated and integrated education involving multiple departments.

Keywords: Generative Artificial Intelligence (GenAI), human-AI collaboration, Generation Z college students, learning behaviors, recommendation-based postgraduate admission policy

1. Introduction

Generation Z, defined here as those born between 1995 and 2009, has become the predominant cohort in higher education. With digital technology shaping cognitive development, their acquisition of knowledge is increasingly characterized by fragmented and decentralized patterns. They pursue personalized self-expression and social interaction within peer communities while also emphasizing authoritative verification and

demonstrating diverse needs. As a result, their learning motivations and cognitive approaches have undergone structural transformation. Specifically, gaining a deeper understanding of the characteristics of Generation Z and systematically advancing educational and pedagogical reform have become pressing priorities. Notably, digital tools represented by GenAI are becoming deeply embedded in the learning process, but their integration does not necessarily lead to a corresponding improvement in learning effectiveness. In an empirical study of interactions between college students and ChatGPT, Zhu Junhua et al. found that the effectiveness of GenAI-enabled learning depends heavily on students' learning readiness, including their prior knowledge, cognitive abilities, and metacognitive level [1]. This finding suggests that, as access to technology has expanded dramatically, the central challenge in learning behaviors has shifted from whether students can access technology to whether they can effectively harness it to achieve deeper cognitive engagement.

Against the strategic framework for building a leading education power during the *15th Five-Year Plan* period, with the priority development of education and moral education as fundamental objectives, China aims to promote the integrated development of education, science and technology, and human resources. Key targets include increasing the average years of education among the working-age population to 11.7 years [2], coordinating the development of universities as the primary force in basic research and as the primary locus for talent cultivation, deepening the integration of industry and education as well as the integration of science and education, establishing university-industry-local government collaborative innovation platforms and flagship initiatives such as innovation competitions for college students [3], and improving systems for the empowerment and commercialization of scientific and technological achievements. Against this backdrop, this study aims to investigate the characteristics of Generation Z college students' learning behaviors in the context of human-AI collaboration, focusing on the complex relationships among digital tool use, perceptions of the recommendation-based postgraduate admission policy, and learning management capabilities. It seeks to uncover the deeper paradoxes underlying technology-enabled learning and provide empirical evidence for more targeted educational reform.

2. Literature review

Against the backdrop of human-AI collaboration, the learning behaviors of Generation Z college students are undergoing structural transformation. Existing research has systematically examined these changes primarily in terms of their characteristics, challenges, and potential responses. First, digital technology has profoundly reshaped learning behaviors and cognitive patterns. Studies consistently indicate that blended learning and coordinated online-offline learning have become commonplace among Generation Z students [4]. This represents more than a change in learning format; it also reflects their fragmented and decentralized cognitive patterns, as well as their high expectations regarding the authority and engaging nature of learning resources [5]. Particularly noteworthy is Generation Z students' ability to spontaneously integrate tools such as generative AI into the learning process for purposes including goal-oriented information seeking, knowledge expansion, and real-time judgment, demonstrating a high degree of technological interactivity and learner agency [1].

From the theoretical perspective of human-AI collaboration, such interactions between individuals and intelligent tools have transcended simple tool use and constitute what distributed cognition theory conceptualizes as a "cognitive partnership". In this relationship, students externalize certain cognitive tasks, such as information retrieval and conceptual explanation, to AI systems, thereby forming a cognitive loop jointly completed by humans and AI [6]. According to the hierarchical classification of human-AI collaboration, students' current use of AI largely remains at the stage of "assistive collaboration", in which AI

provides informational support while humans retain primary responsibility for decision-making. It has not yet broadly progressed to "complementary collaboration" or "generative collaboration", in which humans and AI engage in deep interaction and jointly create solutions to problems. This theoretical framework provides an important reference for understanding the relationship between digital tool use and learning management capabilities in the present study.

However, the digital learning environment has also amplified core challenges such as insufficient self-discipline, weak learning motivation, and emotional detachment. A substantial body of research indicates that insufficient self-discipline is the primary obstacle affecting the effectiveness of online learning [7]. Learning motivation has also been shown to result from complex interactions among students' cognition and behavior and their family, school, and broader social environments [8]. The relative separation between teachers and students and among students themselves in online environments can easily generate feelings of loneliness, thereby placing higher demands on the emotional support provided by teaching and on the quality of interaction.

To assess and improve learning quality, scholars have developed multifactorial models focusing on learning satisfaction and learning engagement. The influence pathway for learning satisfaction has been shown to follow the sequence of "learning interest → classroom performance → learning outcomes → learning satisfaction", with variations according to students' backgrounds [9]. Specifically, in online courses, four key factors have been identified as influencing learning satisfaction: learners' perceived task value, teachers' instructional competence, course content quality, and platform system characteristics [10]. Learning engagement is significantly influenced by online learning readiness and operates partly through mediating variables such as self-efficacy and perceived teacher support [11].

In response to these challenges, educational reform and policy development need to advance in coordination and shift toward systematic, student-centered innovation. Existing research advocates the use of technology to develop deeply blended teaching models characterized by strong interactivity and personalization. This requires comprehensive innovation across the entire educational process, from course design and instructional implementation to quality assessment, supported by whole-process quality assurance frameworks such as the CIPP model [12]. At the same time, macro-level policies, including the recommendation-based postgraduate admission system, should also adapt to these changes. By enhancing transparency and fairness, such policies can more effectively fulfill their functions of motivating students to learn and guiding talent selection [13].

Existing research provides multidimensional perspectives for understanding the learning behaviors of Generation Z, but much of it remains at the level of describing phenomena and lacks an overarching theoretical framework. This study introduces distributed cognition theory and Self-Regulated Learning (SRL) theory as complementary theoretical lenses. Distributed cognition theory holds that cognitive activity does not occur solely within an individual's mind but is also distributed across human-made tools, other people, and the surrounding environment [6]. Accordingly, students can externalize tasks such as information retrieval and conceptual explanation to AI systems, thereby forming a "human-AI cognitive loop". Wang Yonghua et al. further categorize human-AI collaboration into three levels: "assistive collaboration", in which AI provides information while humans retain decision-making authority; "complementary collaboration", in which humans and AI engage in deep interaction; and "generative collaboration", in which humans and AI jointly create new outputs [6]. Most students' current use of AI remains at the first level, providing a theoretical coordinate for understanding the paradox of abundant technological access but limited capability development.

Self-Regulated Learning (SRL) theory, in turn, provides a process-oriented perspective for explaining why the abundance of technology has not necessarily resulted in a corresponding improvement in students'

capabilities. Zimmerman argues that SRL involves a cyclical process of "planning-execution-monitoring-reflection" [14], encompassing metacognitive activities such as goal setting, strategy selection, learning assessment, and content evaluation [1]. Zhu Junhua et al. found that although students frequently use ChatGPT, they remain relatively weak in deeper SRL behaviors, such as formulating learning plans and monitoring learning progress. This is attributable to students' insufficient awareness and ability to integrate technological tools into a complete metacognitive cycle [5].

In summary, this study integrates the levels of human-AI collaboration identified by distributed cognition theory with the process components of SRL to construct an analytical framework. The learning benefits of human-AI collaboration depend on the extent to which AI tools can be embedded within and support the complete SRL cycle. Few existing studies have systematically quantified, from this integrated perspective, the tension between the breadth of tool use and the depth of learning management in the learning behaviors of Generation Z. This study therefore seeks to address this gap.

3. Research design

3.1. Research approach

Drawing on human-AI collaboration theory, this study focuses on Generation Z undergraduate and postgraduate students born between 1995 and 2009. A quantitative empirical analysis was conducted across four dimensions: learning behaviors, awareness of the recommendation-based postgraduate admission policy, preferences for postgraduate institutions, and the use of generative AI tools. The study examines group differences and the mechanisms through which AI empowers college students' learning, and ultimately proposes recommendations for the reform of digital education in higher education institutions.

3.2. Questionnaire design

Drawing on established digital learning scales and adapting them to the research topic, this study developed a questionnaire consisting of 52 items. The questionnaire covered demographic information, four core measurement modules, validity-check items designed to identify inattentive or unreliable responses, and open-ended questions soliciting suggestions. The main scale items were measured using a five-point Likert scale, supplemented by single-choice and multiple-choice questions, thereby accommodating both quantitative analysis and qualitative feedback.

Table 1. Reliability test results for the overall scale

Cronbach's Alpha	Number of Items
0.948	47

Table 2. KMO and Bartlett's test of sphericity

Test	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.949
Bartlett's Test of Sphericity: Approx. Chi-Square	7260.546
Degrees of Freedom	1081
Significance	0

Table 3. Total variance explained (nine factors extracted)

Component	Initial Eigenvalues: Total	Initial Eigenvalues: % of Variance	Initial Eigenvalues: Cumulative %	Extraction Sums of Squared Loadings: Total	Extraction Sums of Squared Loadings: % of Variance	Extraction Sums of Squared Loadings: Cumulative %
1	15.655	33.309	33.309	15.655	33.309	33.309
2	2.727	5.803	39.112	2.727	5.803	39.112
3	2.429	5.168	44.280	2.429	5.168	44.280
4	1.959	4.169	48.449	1.959	4.169	48.449
5	1.348	2.869	51.318	1.348	2.869	51.318
6	1.236	2.630	53.948	1.236	2.630	53.948
7	1.176	2.501	56.449	1.176	2.501	56.449
8	1.134	2.413	58.862	1.134	2.413	58.862
9	1.058	2.251	61.112	1.058	2.251	61.112

Reliability and validity tests were conducted on the 47 items included in the questionnaire, with the results presented in Tables 1–3. The Cronbach's alpha coefficient for the overall scale was 0.948, indicating good internal consistency. The KMO value was 0.949, while Bartlett's test of sphericity yielded a chi-square value of 7260.546, indicating that the data were suitable for exploratory factor analysis. Principal component analysis was employed, and nine common factors with eigenvalues greater than 1 were extracted. The cumulative variance explained by these factors reached 61.112%, indicating that the scale demonstrated good construct validity.

3.3. Data collection

The questionnaire was distributed anonymously online to undergraduate and postgraduate students from various types of higher education institutions. After invalid responses were excluded, 300 valid responses were retained. Anonymity was maintained throughout the data collection process, and respondents' privacy was strictly protected to minimize response bias.

3.4. Data analysis methods

Statistical analyses were conducted using SPSS 26.0. The analytical procedures consisted of the following five steps: (1) reliability and validity analyses to assess the reliability and construct validity of the questionnaire; (2) descriptive statistics and Pearson correlation analysis to examine the overall levels of the variables and their interrelationships; (3) One-way Analysis of Variance (ANOVA) to test differences across groups by gender and place of origin; (4) two-way ANOVA examining the main and interaction effects of year level and academic ranking; and (5) multiple linear regression to identify the key predictors of learning behaviors.

Table 4. Pearson correlations among the four research dimensions ($n = 300$)

Variable			
1. Learning behavior characteristics			
2. Awareness of the recommendation-based postgraduate admission policy and its influence	0.647**		
3. Postgraduate study choices and institutional preferences	0.616**	0.580**	
4. Learning resources and digital tool use	0.633**	0.480**	0.535**

Note: ** indicates that the correlation is significant at the 0.01 level (two-tailed).

As shown in Table 4, all four dimensions were significantly and positively correlated at the 0.01 level, with correlation coefficients ranging from 0.480 to 0.647, indicating moderate-to-strong correlations. These findings suggest a close interrelationship among learning behavior characteristics, awareness of the recommendation-based postgraduate admission policy, postgraduate study choices and institutional preferences, and the use of generative AI and other digital learning tools.

4. Results analysis

4.1. Correlation analysis

Table 5. Correlation analysis

Dimension	Learning Behavior Characteristics	Awareness of and Influence of the Recommendation-Based Postgraduate Admission Policy	Postgraduate Study Choices and Institutional Preferences	Learning Resources and Digital Tool Use
Learning Behavior Characteristics	1	0.647**	0.616**	0.633**
Awareness of and Influence of the Recommendation-Based Postgraduate Admission Policy	0.647**	1	0.580**	0.480**
Postgraduate Study Choices and Institutional Preferences	0.616**	0.580**	1	0.535**
Learning Resources and Digital Tool Use	0.633**	0.480**	0.535**	1

Note: ** indicates that the correlation is significant at the 0.01 level (two-tailed).

A two-tailed Pearson correlation analysis was conducted across the four core research dimensions, with the results presented in Table 5. The results indicate that learning behavior characteristics, awareness of and influence of the recommendation-based postgraduate admission policy, postgraduate study choices and

institutional preferences, and learning resources and digital tool use were all significantly and positively correlated at the 0.01 level. Among these relationships, the correlation between learning behavior characteristics and awareness of and influence of the recommendation-based postgraduate admission policy was the strongest. This indicates that the better Generation Z college students perform in terms of learning behaviors, the greater their awareness of the recommendation-based postgraduate admission policy and the stronger their tendency to engage in learning activities driven by the policy. The moderate-to-strong correlations among the dimensions indicate close underlying relationships among the variables and provide a statistical basis for subsequent multiple linear regression analysis.

4.2. Analysis of between-group effects

Table 6. One-way ANOVA results for differences across gender groups

Dependent Variable	Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>p</i>
Mean score of learning behavior characteristics	0.118	1	0.118	0.115	0.735
Mean score of awareness of and influence of the recommendation-based postgraduate admission policy	2.393	1	2.393	2.209	0.138
Mean score of postgraduate study choices and institutional preferences	0.337	1	0.337	0.596	0.441
Mean score of learning resources and digital tool use	2.031	1	2.031	4.186	0.042

Table 7. One-way ANOVA results for differences across groups by place of origin

Dependent Variable	Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>p</i>
Mean score of learning behavior characteristics (Q8–Q21)	5.775	3	1.925	1.907	0.128
Mean score of awareness of and influence of the recommendation-based postgraduate admission policy (Q22–Q30)	5.314	3	1.771	1.639	0.180
Mean score of postgraduate study choices and institutional preferences (Q31–Q39)	1.061	3	0.354	0.624	0.600
Mean score of learning resources and digital tool use (Q40–Q50)	2.562	3	0.854	1.755	0.156

Table 8. One-way ANOVA results for differences across year levels

Dependent Variable	Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>p</i>
Mean score of learning behavior characteristics (Q8–Q21)	3.001	6	0.500	0.486	0.819
Mean score of awareness of and influence of the recommendation-based postgraduate admission policy (Q22–Q30)	3.696	6	0.616	0.561	0.761
Mean score of postgraduate study choices and institutional preferences (Q31–Q39)	0.489	6	0.082	0.142	0.990
Mean score of learning resources and digital tool use (Q40–Q50)	2.213	6	0.369	0.749	0.611

Table 9. One-way ANOVA results for differences across major-ranking groups

Dependent Variable	Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>p</i>
Mean score of learning behavior characteristics (Q8–Q21)	163.061	4	40.765	84.998	0
Mean score of awareness of and influence of the recommendation-based postgraduate admission policy (Q22–Q30)	74.712	4	18.678	21.989	0
Mean score of postgraduate study choices and institutional preferences (Q31–Q39)	37.997	4	9.499	21.421	0
Mean score of learning resources and digital tool use (Q40–Q50)	32.898	4	8.224	21.338	0

To investigate differences in dimensions related to human-AI collaborative learning among Generation Z college students with different demographic backgrounds, one-way ANOVAs were conducted using gender, place of origin, year level, and academic ranking as grouping variables. The results show that no statistically significant differences were observed across gender, as shown in Table 6, place of origin, as shown in Table 7, or grade-level groups, as shown in Table 8, in any of the four dimensions: learning behavior characteristics, awareness of and influence of the recommendation-based postgraduate admission policy, postgraduate study choices and institutional preferences, and learning resources and digital tool use. In contrast, major-ranking groups, as shown in Table 9, exhibited highly significant between-group effects across all four dimensions ($p < 0.001$). Although the assumption of homogeneity of variance was violated for the learning behavior characteristics dimension, the overall results still indicate that students with higher academic rankings tended to demonstrate stronger human-AI collaborative learning behaviors, greater awareness of the recommendation-based postgraduate admission policy, more developed postgraduate study plans, and greater competence in using digital tools. These findings suggest that academic ranking is a key individual background factor influencing college students' application of generative AI to learning and their perceptions of postgraduate study opportunities, whereas gender, place of origin, and year level do not appear to produce substantial group differentiation.

Table 10. Tests of between-subjects effects I

Source	Type III Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>p</i>
Corrected Model	174.713	34	5.139	10.488	0
Intercept	1,937.225	1	1,937.225	3,954.068	0
Q6_Year Level	1.603	6	0.267	0.545	0.773
Q7_Academic Ranking	131.728	4	32.932	67.217	0
Q6_Year Level $\times$ Q7_Academic Ranking	10.406	24	0.434	0.885	0.623
Error	129.832	265	0.49		
Total	2,812.24	300			
Corrected Total	304.545	299			

Note: $N = 300$; dependent variable: mean score of the learning behavior characteristics dimension; $R^2 = 0.574$, adjusted $R^2 = 0.519$. A p -value < 0.05 indicates a statistically significant difference.

A Two-way Analysis of Variance (ANOVA) was further conducted using year level and academic ranking as the two independent variables, as shown in Table 10, to examine their main and interaction effects on the learning behavior characteristics of Generation Z college students in a generative AI environment. The results show that the main effect of year level was not significant, whereas the main effect of academic ranking was highly significant. The interaction effect between year level and academic ranking was not statistically significant. These findings indicate that academic ranking has a stable effect on students' human-AI collaborative learning behaviors, and this effect does not vary across year levels. In other words, year level and academic ranking do not exert a cumulative or synergistic effect. The model accounted for 51.9% of the variance in learning behavior characteristics after adjustment.

Table 11. Tests of between-subjects effects II

Source	Type III Sum of Squares	<i>df</i>	Mean Square	<i>F</i>	<i>P</i>
Corrected Model	41.240	34	1.213	3.051	0
Intercept	2,056.305	1	2,056.305	5,171.770	0
Q6_Year Level	0.737	6	0.123	0.309	0.932
Q7_Academic Ranking	28.508	4	7.127	17.925	0
Q6_Year Level × Q7_Academic Ranking	7.507	24	0.313	0.787	0.753
Error	105.364	265	0.398		
Total	2,747.174	300			
Corrected Total	146.605	299			

Note: $N = 300$; dependent variable: mean score of the learning resources and digital tool use dimension; $R^2 = 0.281$, adjusted $R^2 = 0.189$. A p -value < 0.05 indicates a statistically significant difference.

A two-way ANOVA was conducted with year level and academic ranking as the independent variables and learning resources and digital tool use as the dependent variable. The results, as shown in Table 11, indicate that the main effect of year level was not statistically significant, whereas the main effect of academic ranking was highly significant. The interaction effect between year level and academic ranking was not significant. These findings suggest that academic ranking significantly predicts students' use of digital learning resources and generative AI tools, and that this effect is not moderated by year level but remains relatively stable across different grade groups. The model explained 18.9% of the variance in this dimension after adjustment.

4.3. Regression analysis

Multiple linear regression analysis was performed with the mean value of the learning behavior characteristic dimension as the dependent variable, as shown in Tables 12-13. The adjusted R^2 of the model was 0.580, indicating that the independent variables collectively explained 58.0% of the variance in learning behaviors. The VIF values of all independent variables were less than 2, suggesting no multicollinearity. Awareness of the recommendation-based postgraduate admission policy, postgraduate study choices and institutional preferences, and learning resources and digital tool use all exerted significant positive predictive effects on the learning behaviors of Generation Z college students. Among them, the dimension of awareness of the recommendation-based postgraduate admission policy yielded the strongest predictive effect, followed by the dimension of learning resources and digital tool use, while the dimension of postgraduate study choices and institutional preferences showed the weakest predictive effect.

Table 12. Coefficients

Model	Unstandardized Coefficient B	Std. Error	Standardized Coefficient Beta	<i>t</i>	<i>p</i>	Tolerance	VIF
(Constant)	-0.457	0.176		-2.593	0.010		
Awareness of and influence of the recommendation- based postgraduate admission policy	0.338	0.046	0.349	7.363	0	0.624	1.604
Postgraduate study choices and institutional preferences	0.310	0.066	0.230	4.677	0	0.578	1.730
Learning resources and digital tool use	0.493	0.066	0.342	7.476	0	0.670	1.492

Note: Dependent variable: mean score of the learning behavior characteristics dimension; $N = 300$.

Table 13. Model summary

Model	<i>R</i>	<i>R</i> ²	Adjusted <i>R</i> ²	Std. Error of the Estimate
1	0.765	0.585	0.580	0.654

5. Recommendation and policy implication

Building on the stratified empowerment patterns, multidimensional linkage mechanisms, differentiated effects of year level and academic ranking, and practical challenges identified in this empirical study—including the superficial application of generative AI and information asymmetry in postgraduate study opportunities—this study proposes targeted optimization strategies from the perspective of human-AI collaborative education. These strategies address four major areas: higher education teaching reform, academic development guidance, digital literacy development, and postgraduate admission and progression services, with the aim of fully realizing the potential of generative AI to empower Generation Z college students' learning.

First, establish a stratified and precision education system to address group disparities in human-AI collaborative learning.

The findings demonstrate significant differences in learning and digital tool use associated with academic ranking, place of origin, and gender, while year level does not produce an independent improvement effect. Simply opening up access to AI tools may therefore exacerbate academic stratification. Higher education institutions should develop differentiated training programs based on students' academic rankings. For students with middle and lower academic rankings, universities should establish regular small-group digital learning support sessions and assign academic mentors to guide them in using generative AI to identify key and difficult points in their courses and construct knowledge frameworks, thereby addressing deficiencies in foundational learning capabilities. For students from county-level areas and male students, universities should simultaneously disseminate information on recommendation-based postgraduate admission policies, target institutions, and application requirements through specialized lectures, online study communities, and one-to-one peer mentoring, thereby narrowing the dual gaps in digital literacy and access to postgraduate study

information. Universities should also abandon the passive assumption that senior students will develop independently. Instead, a foundational compulsory module on human-AI collaborative learning should be offered to students at all year levels, with digital learning habits cultivated from the early undergraduate years and reinforced upon entry into postgraduate study. This would help prevent academically disadvantaged groups at different stages of study from becoming trapped in long-term patterns of underutilized learning resources and inadequate postgraduate study planning.

Second, target the core demand for postgraduate progression and promote the deep integration of generative AI with academic development.

The regression analysis shows that awareness of the recommendation-based postgraduate admission policy is the strongest positive predictor of students' learning behaviors. The pursuit of postgraduate study opportunities is a core motivation driving Generation Z college students' use of digital tools, suggesting that AI-related educational training detached from students' actual postgraduate study needs may be difficult to sustain. On the one hand, practical training in generative AI tools should be embedded throughout the entire process of policy communication, preparation for recommendation-based postgraduate admission, competitions, and research activities. Universities could develop an AI-powered intelligent interpretation platform for recommendation-based postgraduate admission policies that automatically matches students' academic rankings and eligibility for additional points and generates personalized postgraduate study planning recommendations. AI could also assist students in refining competition applications, course papers, and research literature reviews, thereby using students' intrinsic motivation for postgraduate progression to stimulate active engagement in human-AI collaborative learning. On the other hand, universities should improve digital support services for the recommendation-based postgraduate admission process. AI can be used to integrate information on recommendation quotas, assessment criteria, and supervisors' research areas across different institutions and to establish a cross-university information retrieval and matching system. Such a system could alleviate information asymmetry when students select prospective institutions and maximize the potential of generative AI as a tool for reducing information gaps in postgraduate study planning.

Third, establish an integrated digital literacy development mechanism to enhance Generation Z college students' higher-order human-AI collaborative capabilities.

Among the surveyed students, the use of generative AI is currently concentrated largely in superficial applications such as conceptual explanations and assignment writing, while higher-order applications in research innovation and knowledge-system review remain underdeveloped. At the same time, digital tool use, postgraduate study planning, and learning behaviors exhibit significant positive linkages, indicating that training in isolated skills cannot achieve comprehensive empowerment. Universities should coordinate the development of standardized digital learning resource repositories integrating MOOCs, disciplinary databases, and guidelines for the compliant use of generative AI tools. Tiered digital literacy courses should be offered, with lower-year students focusing on basic AI operations, time management, and online resource retrieval, while senior undergraduates and postgraduate students develop higher-order human-AI collaborative skills in AI-assisted research design, literature synthesis, and academic innovation. Universities should also improve the operation of online learning communities and virtual study rooms, encouraging students to use AI for group discussions, resource sharing, and learning reflection, thereby developing a new learning model characterized by "self-directed learning, AI assistance, and peer collaboration". At the same time, clear guidelines should be established for the academic use of generative AI, specifying the boundaries of AI-assisted applications in academic writing and course assignments while balancing the efficiency of digital learning with the cultivation of academic integrity.

Fourth, establish a coordinated educational mechanism integrating policy education, postgraduate study planning, and digital empowerment to overcome the fragmentation of single-module educational interventions.

The correlation analysis indicates that learning behaviors, awareness of recommendation-based postgraduate admission policies, institutional preferences, and digital tool use form an interconnected system. Conducting policy communication, postgraduate study guidance, or AI training in isolation is therefore unlikely to maximize educational outcomes. Universities should integrate resources from multiple administrative units, including academic affairs offices, graduate schools, student affairs offices, and information technology centers, to establish an integrated academic development service platform. Academic affairs offices should be responsible for guiding classroom learning behaviors and advancing the digital transformation of routine teaching; graduate schools should provide regular interpretation of recommendation-based postgraduate admission policies, promote undergraduate-to-postgraduate articulation policies, and offer guidance on institutional selection; information technology centers should continuously update digital learning tools and optimize supporting functions for AI-assisted teaching; and student affairs personnel should provide ongoing career planning and psychological support. Specialized guidance should be provided to students with different aspirations, including those seeking to remain at their current institutions for postgraduate study and those planning to pursue postgraduate education at other institutions. AI tools can be used to help students compare institutional strengths and weaknesses, supervisor resources, and potential development pathways, thereby enabling classroom learning improvement, understanding of postgraduate admission policies, and digital tool use to progress simultaneously and reinforce one another.

Fifth, improve supporting hardware and software infrastructure to strengthen the foundation of the human-AI collaborative learning environment.

In response to students' needs for learning spaces, teaching resources, and academic development guidance identified through the open-ended questionnaire items, universities should optimize both physical and digital learning environments. On the one hand, they should expand the provision of offline learning spaces by increasing library capacity and specialized study rooms, equipping them with digital learning terminals, and maintaining virtual study rooms to accommodate diverse learning scenarios. On the other hand, universities should continuously enrich high-quality online disciplinary resources, increase the availability of interdisciplinary online courses and research training projects, and provide corresponding guidance on learning strategies and stress management to alleviate anxiety arising from the intense competition for postgraduate study opportunities among Generation Z college students. In the long term, universities should continuously monitor the effectiveness of human-AI collaborative learning among different student groups and regularly conduct surveys and focus-group discussions. Based on the findings, they should dynamically adjust the provision of digital resources, recommendation-based postgraduate admission services, and course content, thereby establishing a closed-loop educational reform mechanism encompassing research, policy implementation, and feedback. This mechanism can support the continuous optimization of pathways for leveraging generative AI to empower college students' learning.

6. Conclusion

Based on human-AI collaboration theory and distributed cognition theory, this study empirically investigates the internal mechanism of how GenAI empowers college students' learning using 300 questionnaire samples from Generation Z undergraduate and postgraduate students. The findings are as follows. First, Generation Z college students mostly apply GenAI at the superficial auxiliary-collaboration stage for tasks such as assignment assistance, and have not yet achieved in-depth human-AI complementarity and co-creation.

Demands for postgraduate recommendation serve as the core motivation driving their digital learning. Second, the four dimensions--learning behavior characteristics, awareness of the recommendation-based postgraduate admission policy, postgraduate study choices and institutional preferences, and learning resources and digital tool use--are significantly and positively correlated in pairs, forming a closely coupled interactive relationship. Third, gender, place of origin and year level produce no significant group differences in the above-mentioned learning dimensions. Academic ranking acts as a key stratifying variable, which exerts a stable cross-grade positive effect on college students' human-AI collaborative learning behaviors, awareness of postgraduate recommendation policies, postgraduate study planning and AI tool use, while year level has no independent moderating effect. Fourth, awareness of the recommendation-based postgraduate admission policy, postgraduate study choices and institutional preferences, as well as learning resources and digital tool use can positively predict college students' learning behaviors, among which awareness of the recommendation-based postgraduate admission policy yields the strongest predictive effect. Simply granting open access to AI tools tends to aggravate academic stratification, and digital literacy cannot be naturally improved with grade progression.

In summary, the empowering effect of GenAI on Generation Z college students' learning is not directly determined by technological tools per se, but is constrained by students' motivation for postgraduate study, academic foundation and the level of human-machine collaborative application. Universities cannot realize educational value merely through technology provision. Instead, they should implement targeted stratified education combined with students' further-education demands, promote staged cultivation of digital literacy, integrate policy popularization, further-education guidance and digital competence training, and construct an integrated multi-department collaborative education system. These measures can avoid the risk of academic stratification brought by technology and give full play to the educational effectiveness of human-AI collaboration.

Fundings

Beijing International Studies University Graduate Education and Teaching Reform Research Project: Construction of an "One-Entity, Two-Element and Three-Dimension" Curriculum-Based Ideological and Political Education System for the Tourism Management Program and Research on Graduate Student Satisfaction (11122025501); Beijing International Studies University General Education and Teaching Reform Research Project: Research on an Integrated and Coordinated Training Mechanism for Undergraduate and Graduate Students in the Context of the New Liberal Arts (11010072133)

References

- [1] Zhu, J., Xu, L., & Ma, J. (2025). How does generative artificial intelligence facilitate student learning: An empirical investigation on self-regulated learning behaviors of undergraduates. *Research in Higher Education of Engineering*, (2), 66–72.
- [2] Ministry of Education of the People's Republic of China. (2026, March 14). *What should be done in education during the 15th Five-Year Plan period*. Ministry of Education of the People's Republic of China.
- [3] Central Committee of the Communist Party of China, & State Council of the People's Republic of China. (2025, January 19). *Outline of the plan for building China into a leading country in education (2024–2035)*. State Council of the People's Republic of China.
- [4] Du, Y., Han, J., Yang, S., Wang, L., & Zhang, H. (2022). A study on the impact of Internet use on college students' learning: The case of economics majors. *University Education*, (3), 132–135.

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- [5] Xing, Z. (2025). The impact of the multidimensional characteristics of online education courses on college students' intention to continue learning. *Theory and Practice of Education*, 45(18), 61–64.
- [6] Wang, Y., Yin, X., & Li, W. (2026). Knowledge learning in the era of human-machine symbiosis: Essence, paradigm, and educational responses. *Modern Educational Technology*, 36(4), 15–22.
- [7] Li, Y., Chen, X., Chen, Y., Zhou, Q., & Wang, J. (2020). Survey and implications of college students' online learning during the COVID-19 pandemic: A case study of Zhijiang College, Zhejiang University. *Open Education Research*, 26(5), 60–70.
- [8] Liu, J., Fu, Y., Zong, T., Zhang, W., & Li, M. (2019). A study of the factors underlying the lack of college students' learning motivation and strategies for enhancement from the perspective of Bandura's social learning theory. *Jiangsu Science and Technology Information*, 36(28), 49–52.
- [9] Wen, C., & Shi, Q. (2023). An analysis of the current status and influencing mechanisms of college students' satisfaction with ideological and political theory courses across different backgrounds: Based on the National College Student Survey (NCSS). *Education Research Monthly*, (8), 57–64.
- [10] Shi, Y., Pu, Q., Qu, Z., Liu, X., & Zhao, Y. (2023). The current status, influencing factors, and improvement strategies of learning satisfaction with online course resources. *Modern Educational Technology*, 33(3), 91–99.
- [11] Rao, A., & Wan, K. (2020). A study on the influence of online learning readiness on college students' online learning engagement. *Education Science*, 36(2), 31–38.
- [12] Li, Y., & Wang, F. (2024). Construction of a CIPP-based quality assurance framework for college students' online course learning. *Heilongjiang Researches on Higher Education*, 42(11), 148–154.
- [13] Peng, Y., & Zhou, X. (2026). The evolution of the recommendation-based admission system for master's students since the founding of the People's Republic of China. *Higher Education Development and Evaluation*, 1–12.
- [14] Zimmerman, B. J., & Schunk, D. H. (2001). *Self-regulated learning and academic achievement* (2nd ed.). Lawrence Erlbaum Associates.