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Research on the Impact of Generative Artificial Intelligence on the Talent Training Model for New Business Disciplines in Application-Oriented Undergraduate Education

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Abstract: With the continuous development of new business education demands, traditional education models face numerous challenges, particularly exhibiting significant shortcomings in cultivating inter-disciplinary talent that meets the requirements of the digital economy era. Existing teaching methods fail to effectively integrate modern technology, especially showing obvious limitations in personalized learning and real-time feedback, regarding the promotion of students' innovation ability, learning motivation, and academic performance. This paper introduces generative artificial intelligence technology, particularly AI tools like Chatgpt or Deepseek, to explore its application in new business education, aiming to address issues such as low knowledge transfer efficiency and poor interactivity in traditional teaching models. By combining artificial intelligence with traditional teaching methods, this paper constructs a novel educational model with the primary goals of enhancing learning motivation, learning outcomes, and self-directed learning ability. In the experiment, AI tools not only provide personalized learning paths but also implement a real-time feedback mechanism, helping students make precise corrections regarding weaknesses in their learning. The results show that the experimental group's learning motivation score demonstrates a prominent change between pre- and post-test measurements. The pre-test scores for learning motivation in the experimental group range from 3.5 to 3.9, while the post-test scores increase significantly to 4.2 to 4.6, indicating a marked improvement. This suggests that AI tools play an important role in stimulating students' learning interest and engagement.

1. Introduction

With the rapid development of the digital economy and emerging technologies, business education faces unprecedented transformation. Traditional education models focus on the transmission of single-discipline knowledge, struggling to meet the demand from enterprises and society for inter-disciplinary talent possessing cross-disciplinary capabilities. Simultaneously, the widespread application of new technologies such as artificial intelligence and big data provides new opportunities for innovation in teaching models. Generative artificial intelligence tools, like ChatGPT and Deepseek, can play significant roles in generating learning content, facilitating interactive communication, and providing personalized feedback, offering students more efficient learning experiences and pathways for enhancing practical abilities.

Therefore, this paper aims to explore the practical impact of integrating generative artificial intelligence technology with the new business education model on the cultivation of students' comprehensive abilities. Through empirical data analysis, it seeks to verify the effectiveness of AI-assisted teaching in enhancing learning motivation, academic performance, and innovation capability, providing a theoretical basis and practical reference for the reform of new business education in application-oriented undergraduate institutions.

2. Related Works

Against the backdrop of global digital transformation and complex business environments, research on the cultivation of interdisciplinary talent and management strategies receives increasing attention from both enterprises and educational institutions.

Huiqi emphasized interdisciplinary integration and professional convergence to cultivate compound business talents with knowledge related to the digital economy and cross-disciplinary abilities, integrating emerging technologies like big data and artificial intelligence to strengthen practice orientation and collaborative learning [1]. Orea et al. conducted an empirical analysis of the relationship between business models and employment evolution during the Great Recession. This study clearly confirmed that talent integration into organizations impacts performance through a solid value proposition that is scalable and adaptable to environmental changes, with its transformation necessarily led by top management [2]. Kandukuri researched the causes of talent drain and the importance of sustainable human resource practices, such as talent management and its alignment with business. He highlighted why small and medium-sized enterprises (SMEs) experience higher talent turnover rates compared to larger enterprises adopting higher quality and more economical talent management practices [3]. Arrosyid and Wahyuningtyas examined the separate and combined effects of training and digital culture on enhancing developer capability. The study found that training has a significant positive impact on capability ($\theta = 0.217$; $p = 0.013$), although its degree of influence is moderate. In contrast, the impact of digital culture is more significant ($\theta = 0.725$; $p = 0.000$) and has a larger effect size ($f^2 = 0.415$) [4]. By using an organized review of the literature backed by qualitative content evaluation, Yildiz and Esmer were able to determine which Talent Management (TM) strategies were most prevalent in the current literature. They also found that, from 2006 to July 2022, the most talked-about topics in the field were talent retention strategies, followed by talent preparation and talent development methods [5]. Yildiz et al. proposed implementing cross-cultural training programs, establishing global leadership pipelines, utilizing advanced talent analytics techniques, and formulating flexible HR policies to adapt to different local conditions for global talent management [6]. In order to increase employee retention rates, Urme's research emphasized the significance of tactics like thorough hiring and selection processes, training and development initiatives for staff members, performance monitoring and feedback systems, competitive pay and benefits, and cultivating a positive workplace culture [7]. Nieto-Aleman et al. used fuzzy-set Qualitative Comparative Analysis (fsQCA) to analyze causal patterns leading to high talent management performance in SMEs. The results indicated that high talent management performance is not determined by a single condition [8]. Kafetzopoulos combined a literature review with exploratory interviews with managers and scholars. The results showed that talent development positively influences strategic flexibility and innovation capability. Furthermore, strategic flexibility is a crucial capability for corporate innovation and financial performance [9]. Sigala et al. adopted a phenomenological approach, analyzing data collected through semi-structured interviews with a representative sample of 20 hotel managers in Macau. The study found that four contingent TM practices—contingent TM planning, contingent TM deployment and replacement, talent training and development under contingent arrangements, and 'talent' attitudes and practices in recruitment and retention—help shape the next new normal of TM in the hotel industry [10]. Ganiyu et al. looked at the efficacy of a virtual training program conducted by a public establishment in South Africa during a crisis period, using a classified random sampling procedure to select those responding (employees receiving online training and trainers providing instructions during the crisis). The above results demonstrated the influence of insights technology and virtual instruction platforms on the one that powers the effectiveness of the virtual training program in the southern portion of Africa during the pandemic [11]. Although existing research systematically explores various strategies for talent cultivation and management, significant deficiencies remain in terms of interdisciplinary integration, the application of digital technologies, and the validation of practical effects.

3. Methods

3.1 Characteristics of Talent Training for New Business Disciplines

New business disciplines integrate subjects such as applied economics, management, computer science, and artificial intelligence. They focus on combining new technologies with new business models and emphasize cultivating commercial abilities and practical skills required for the digital economy era. These disciplines possess both practicality and scientific rigor, closely integrating new theories with practical applications. The establishment of new business disciplines aims to meet society's demand for inter-disciplinary talent while breaking through the boundaries of traditional business education.

Compared to comprehensive research-oriented universities, local application-oriented undergraduate institutions exhibit more regional and application-oriented characteristics in talent training. The focus lies on serving local economic and social development and providing usable talent for regional industries.

3.2 The "Mismatch" Dilemma between Talent Supply and Demand

Although cooperation between universities and enterprises continues to increase, the current forms of collaboration primarily remain at superficial levels such as internship-based and enterprise lectures, lacking deep integration. The insufficient introduction of real enterprise projects leaves students with few practical operation opportunities, leading to a disconnect between theory and practice.

The development of new, quality productive forces brings forth many new business models and formats, placing higher demands on business talent. However, traditional business education still shows deficiencies in multidisciplinary integration. Curriculum design and specialization divisions primarily follow traditional models, with limited integration of emerging technology courses such as artificial intelligence and big data analytics, making it difficult to meet the training needs for interdisciplinary talent in the digital economy. Simultaneously, lagging phenomena also exist in aspects such as program establishment and teaching content. Currently, the business course systems in many universities update on a 3-5 year cycle, struggling to adapt to the talent capability demands driven by new technologies and business formats. This lag directly results in a mismatch between graduates' knowledge structures and societal needs, exhibiting a significant "mismatch" in both knowledge structure and the quality of talent supply.

3.3 Application of "Large Class Teaching + Small Class Seminars" in the Integration of Industry and Education for Accounting and Finance Majors

In classroom teaching, the traditional "cramming" method of teaching should be broken, and the classroom should serve as a platform for cultivating students' comprehensive abilities. The "large class teaching + small class seminars" model combines the teacher's professional knowledge transmission with students' understanding and expansion of the course content.

During the "large class teaching" phase, the teacher explains the knowledge points required by the syllabus according to the course schedule, focusing on principles, core content, and difficulties, while also imparting methods for acquiring knowledge and information. After completing a unit's content, the large class is divided into several small classes for "small class seminars." Small classes conduct discussions in group format, preferably using a round-table style to ensure every student has the opportunity to speak.

To ensure the effectiveness of small class seminars, the teacher needs to assign basic and in-depth learning tasks after class, allowing students to form group opinions through consultation, discussion, and exchange, which are then shared during the seminar sessions. This model helps enhance students' learning ability, communication skills, innovation capability, and social adaptability, serving as an important pathway for cultivating high-quality application-oriented talent.

3.4 Shaping New Learning Modalities

ChatGPT, Deepseek, and similar tools are important components of the digital education system, providing comprehensive support for personalized learning. This includes rapid generation of learning content, learning interaction, learning assessment, and whole-process companionship, supporting competency-based self-directed learning and enabling students to set ability goals and receive personalized improvement plans. By analyzing student grades and learning performance, teachers can provide corresponding feedback to assist students in achieving their goals. Comprehensive monitoring occurs through an efficient, scientific, and personalized learning cycle of "preparation-learning-assessment-feedback," providing timely support to maintain student learning enthusiasm. Generative artificial intelligence enables interaction between humans and AI, forming a new mode of interaction.

When handling large-scale, repetitive, and structured tasks, generative AI tools demonstrate characteristics of high efficiency and accuracy. However, due to factors such as dataset quality and training methods, the reliability and practicality of the generated content possess uncertainty. Therefore, intelligent tools cannot complete tasks alone; they must cooperate with humans to jointly enhance efficiency and quality. During the cooperation process, humans play a leading role in aspects such as emotional communication and value judgment, while intelligent tools provide auxiliary support.

3.5 Constructing an E-Commerce Professional Teaching Model Adapted to the Development of New Quality Productive Forces

High-quality e-commerce development can accelerate the development of new, quality, productive forces. Utilizing generative artificial intelligence technology (e.g.,Deepseek) to advance e-commerce teaching methods can innovate the teaching content and methods for theoretical knowledge and practical skills. Through AI technology, students can master the practical operation of knowledge, engage in independent thinking and practice based on digital technology, and fully experience the teaching assistance functions of generative artificial intelligence.

By collaborating with AI platforms to conduct teaching activities, students can clearly understand platform usage norms and functions. Under the premise of setting Deepseek permissions, its advantages are leveraged to strengthen the allocation of professional educational resources and course scheduling, achieving centralized optimization of educational resources. Furthermore, platforms like Deepseek and ChatGPT can be used to develop more "golden course" resources, enhancing student learning interest. Simultaneously, teachers can use AI to collect and analyze data, more scientifically formulate teaching plans, supervise classrooms, track student thought dynamics, and assess grades, helping students better master knowledge and skills.

3.6 Innovating the AI-Empowered Human resource management Teaching Method System

Supported by generative artificial intelligence technology, the traditional single-teacher model transforms into a diversified AI teaching system capable of comprehensively monitoring student learning throughout the entire Human resource management teaching process. Under the model where humans are primary and technology is auxiliary, generative AI provides teachers with diverse teaching tools and management methods, such as intelligent lesson preparation, precise feedback on student learning situations, and adjustment of teaching plans, aiding the realization of "teaching students according to their aptitude." AI can serve as a teaching assistant to optimize courses, transforming the teacher-student relationship from a binary "teacher-student" structure to a ternary "human teacher-machine teacher-student" structure.

The Human resource profession should establish educational teams primarily composed of smart human resource management talent, providing students with cutting-edge academic perspectives and technical guidance. To adapt to the development of the digital economy, Business Administration Major collaborate with enterprises to develop "Smart Human Resource Sharing" courses, constructing practical platforms. Through these platforms, students can personally experience the entire process of enterprise human resource management, including human resourcel data analysis, business process prediction, and real-time decision optimization, thereby understanding the pathways to utilizing digital technology for solving human resource problems.

4. Results and Discussion

4.1 Experimental Group and Control Group

Experimental Group: Students who use generative artificial intelligence tools to assist their learning.

Tools Used: Generative AI tools like Deepseek, assisting students with content creation, problem-solving, personalized learning path recommendations, etc.

Control Group: Students who use traditional teaching methods.

Without using generative artificial intelligence tools, regular teaching activities are carried out relying on teacher lectures and teaching materials.

4.2 Course Content

A core course related to new business disciplines (such as "Digital human resource management “or” Training Data Analysis and Decision Making") is selected for teaching both the experimental and control groups.

The experimental group uses generative artificial intelligence tools to assist learning, such as after-class question and answer sessions, simulated case analysis, and automated feedback.

The control group relies on traditional classroom learning and textbooks, lacking the assistance of intelligent tools.

Each student needs to complete a series of after-class tasks, such as case analyses, data reports, business simulations, etc.

Students in the experimental group can use generative AI tools for data analysis, scheme design, content creation, etc., and interact with AI to enhance learning depth.

Students in the control group rely on traditional methods to complete tasks, receiving guidance and feedback from the teacher.

4.3 Timeline

Preliminary Preparation (1 week): A baseline assessment is conducted for all participating students before the experiment, including evaluations of learning motivation, knowledge level, and skills.

Experimental Phase (8 weeks): Course teaching is conducted. The experimental group uses generative AI tools continuously for learning and task completion.

Post-assessment (1 week): Students are assessed again after the course concludes, and data on learning outcomes are collected.

4.4 Experimental Evaluation Metrics

Learning Motivation: A scale measures students' learning interest, sense of participation, and self-efficacy.

For example, the Motivated Strategies for Learning Questionnaire (MSLQ) is used to assess changes before and after the experiment.

Learning Outcomes: Final exam scores, assignment grades, and case analysis results assess students' mastery of knowledge and application abilities.

For example, a grading rubric evaluates students' submitted business analysis reports.

Self-Directed Learning Ability: It measures whether students can complete tasks independently without teacher help.

A self-directed learning ability assessment scale evaluates changes in students' autonomous learning ability before and after the experiment.

Collaboration Ability: It observes students' cooperation in team tasks, assessing their teamwork, communication, and problem-solving skills.

Innovation Ability: It evaluates students' innovative thinking through the innovative solutions they propose in practical cases.

A comparison of innovation capability can be conducted by analyzing differences between solutions generated using AI tools and traditional solutions.

4.5 Data Analysis Methods

Quantitative Analysis:

SPSS or R software is used for data analysis. T-tests, analysis of variance (ANOVA), and other methods are employed to conduct statistical tests on the differences between the experimental and control groups across various evaluation indicators.

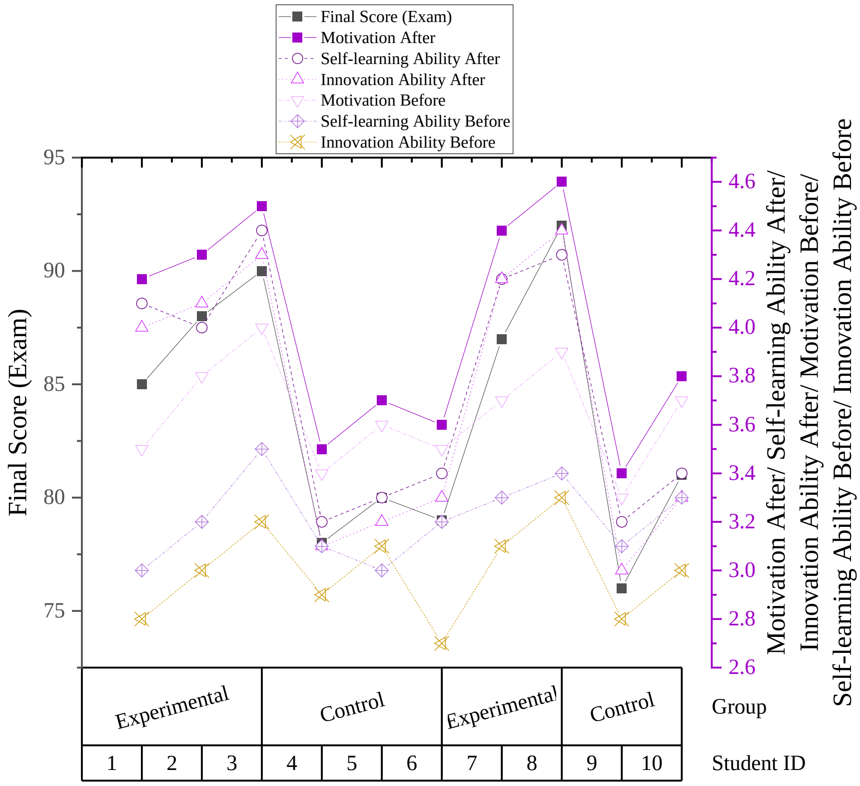

Figure 1. Assessment of Learning Motivation, Learning Outcomes, Self-Directed Learning Ability, and Innovation Ability

Table 1. T-test Results (Independent Samples T-test)

Evaluation Indicator	t-value	Degrees of Freedom (df)	p-value	Conclusion
Motivation (Pre-Post Change)	3.72	18	0.002	Significant difference ($p < 0.05$)
Learning Outcome (Final Score)	2.35	18	0.03	Significant difference ($p < 0.05$)
Self-learning Ability (Pre-Post)	1.45	18	0.17	No significant difference ($p > 0.05$)
Innovation Ability (Pre-Post)	4.15	18	0.001	Significant difference ($p < 0.05$)

The experimental group's learning motivation score demonstrates a prominent change between pre- and post-test measurements. The pre-test scores for learning motivation in the experimental group range from 3.5 to 3.9, while the post-test scores increase significantly to 4.2 to 4.6, indicating a marked improvement. This suggests that AI tools play an important role in stimulating students' learning interest and engagement. Particularly for students with ID numbers 7 and 8, the improvement in learning motivation rises from 3.7 and 3.9 to 4.4 and 4.6, indicating that generative AI tools are especially effective in enhancing student learning motivation. The experimental group's final scores are generally higher, ranging from 85 to 92, significantly improved compared to the control group's range of 76 to 81. The experimental group's students generally show clear improvement in their self-directed learning ability scores between pre- and post-test measurements, rising from the preliminary range of 3.0-3.5 to 4.1-4.3. This indicates that generative AI tools promote students' self-directed learning ability, helping them better master learning content and find answers independently (as shown in Figure 1).

The significant differences between the experimental and control groups in terms of learning outcomes, learning motivation, self-directed learning ability, and innovation ability are analyzed.

According to the results of the independent samples t-test in Table 1, the experimental and control groups show significant differences in multiple evaluation indicators, especially in learning motivation, learning outcomes, and innovation ability. The change score (pre-post) for learning motivation in the experimental group is significantly higher than that of the control group, with a t-value of 3.72 and a p-value of 0.002 ($p < 0.05$), demonstrating the effective role of generative AI tools in enhancing student learning enthusiasm and participation. The learning outcomes (final scores) of the experimental group are also significantly better than those of the control group, with a t-value of 2.35 and a p-value of 0.03 ($p < 0.05$), indicating that AI-assisted teaching can promote improvement in academic performance. The improvement in innovation ability score is most significant for the experimental group, with a t-value of 4.15 and a p-value of 0.001 ($p < 0.05$), further proving the positive impact of generative AI tools on stimulating students' innovative thinking and practical ability. Although the self-directed learning ability of the experimental group improves, the t-value is 1.45 with a p-value of 0.17 ($p > 0.05$), not reaching a significant level, indicating that the improvement in this indicator is relatively limited. Overall, the t-test results show that AI-assisted teaching can significantly improve the performance of students in the experimental group on key indicators such as learning motivation, learning outcomes, and innovation ability, highlighting the potential value of generative artificial intelligence in reforming the new business education model.

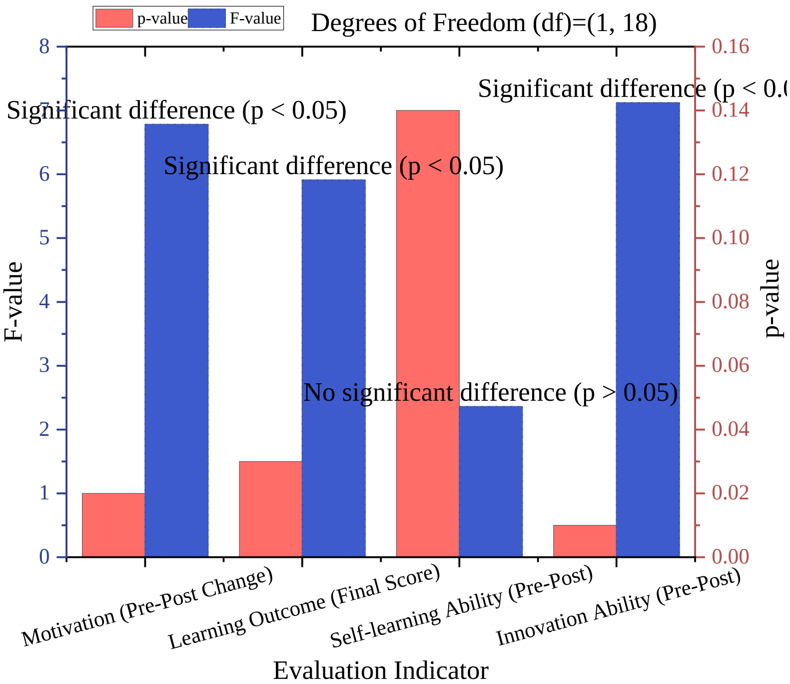

Figure 2. Analysis of Variance (ANOVA) Results

Judging from the results of analysis of variance (ANOVA), there are significant differences between the experimental group and the control group in multiple evaluation indicators. In particular, in terms of learning motivation, learning effect and innovation ability, the experimental group performs significantly better than the control group, as shown in Figure 2.

The ANOVA results show an F-value of 6.78, degrees of freedom (df) of 1, 18, and a p-value of 0.02, indicating a significant difference between the experimental and control groups in the change of learning motivation ($p < 0.05$). The experimental group's learning motivation score increases from 3.5 to 4.4, demonstrating the effective role of generative AI tools in enhancing student learning motivation and stimulating a sense of participation. Although the change in self-directed learning ability for the experimental group shows some improvement, the ANOVA results show an F-value of 2.36 and a p-value of 0.14, indicating that the difference in the change of self-directed learning ability between the experimental and control groups does not reach statistical significance ($p > 0.05$). Even though the experimental group's self-directed learning ability score increases from 3.0-3.5 to 4.1-4.3, showing some improvement, it does not reach statistical significance. This suggests that the effect of generative AI tools in promoting self-directed learning might be relatively limited.

Qualitative Analysis:

Through student interviews and questionnaire feedback, their usage experience, feelings regarding generative AI tools, and practical application in learning are analyzed.

Student preferences for traditional teaching methods versus AI-assisted teaching methods, as well as subjective evaluations of teaching quality and learning outcomes, are compared.

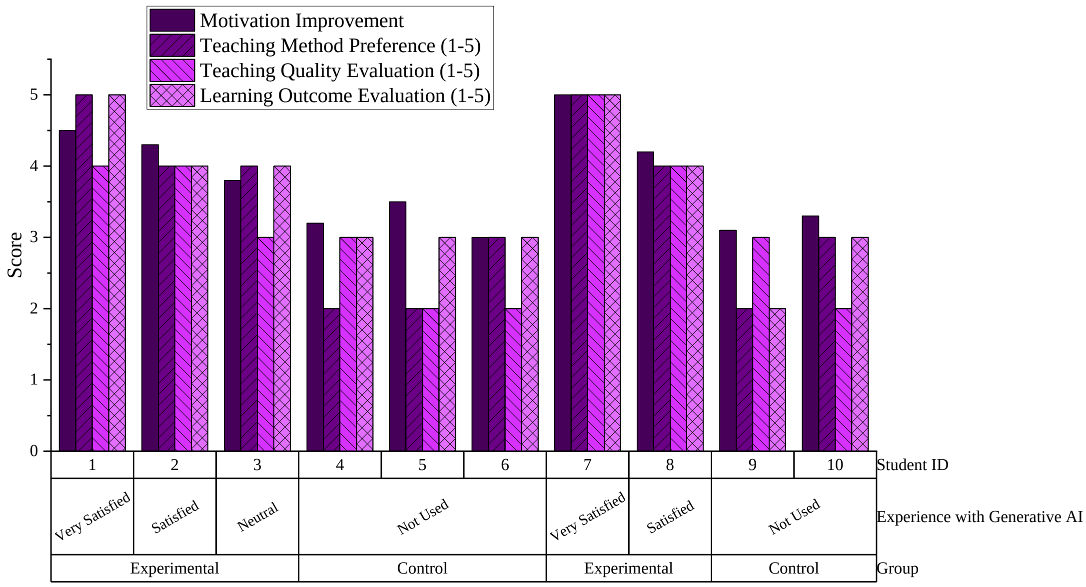

Figure 3. Student Interviews and Questionnaire Feedback

From the student interview and questionnaire feedback data, the experimental group students generally report positive experiences with using generative AI tools. Significant positive changes are observed in aspects such as learning motivation, teaching method preference, teaching quality evaluation, and learning outcome evaluation. The improvement in learning motivation among experimental group students is generally high, with scores ranging from 3.8 to 5.0. Students with ID numbers 1 and 7 give very high ratings (4.5 and 5), indicating they believe generative AI tools significantly enhanced their learning motivation. The learning motivation improvement ratings of other experimental group students are also relatively high (scores 4.2-4.3), showing the effectiveness of AI tools in enhancing student learning enthusiasm. Regarding teaching method preference, experimental group students show high preference scores, generally above 4, ranging from 4 to 5. Students with ID numbers 1 and 7 give the highest rating (5) to the AI-assisted teaching method, believing that generative AI tools greatly facilitated their learning experience. In contrast, the teaching method preference of control group students is lower, with scores generally between 2 and 3, indicating their preference leans towards traditional teaching methods, as shown in Figure 3.

5. Conclusion

This paper systematically investigates the role of introducing generative artificial intelligence technology into application-oriented undergraduate new business education in enhancing students' learning motivation, learning outcomes, self-directed learning ability, and innovation capability. Although the research yields positive results, certain limitations exist. Firstly, the experimental sample size is limited, and the research subjects are primarily concentrated in a single institution, so the generalizability of the results requires further verification. Secondly, the control of external variables such as teacher proficiency and course content in the experimental design needs strengthening. Future research can conduct multi-center experiments in broader educational environments, combining more qualitative and quantitative analysis methods to further explore the application potential of generative artificial intelligence in interdisciplinary curriculum design, practical project guidance, and personalized learning path construction, thereby promoting the continuous optimization and innovative development of the new business education model.

References

[1]Huiqi L. Analysis of the Reform of the New Business Talent Training Model[J]. Analysis of the Reform of the New Business Talent Training Model, 2025, 7(1): 6-9.

[2]Orea A, del Val M T, García C. The talent management business model and its impact on business performance[J]. Journal of Enterprising Communities: People and Places in the Global Economy, 2025, 19(1): 23-43.

[3]Kandukuri V. Aligning talent and business: A key for sustainable HRM in SMEs[J]. Journal of Entrepreneurship and Innovation in Emerging Economies, 2023, 9(1): 80-91.

[4]Arrosyid M S, Wahyuningtyas R. The Influence of Training and Digital Culture on The Capabilities of Developer Talent: A Case Study of PT. XYZ[J]. American Journal of Economic and Management Business (AJEMB), 2025, 4(8): 1197-1210.

[5]Yildiz R O, Esmer S. Talent management strategies and functions: a systematic review[J]. Industrial and commercial training, 2023, 55(1): 93-111.

[6]Uzozie O T, Onukwulu E C, Olaleye I A, et al. Global talent management in multinational corporations: Challenges and strategies–A systematic review[J]. International Journal of Multidisciplinary Research and Growth Evaluation, 2023, 4(1): 1095-1101.

[7]Urme U N. The impact of talent management strategies on employee retention[J]. International Journal of Science and Business, 2023, 28(1): 127-146.

[8]Nieto-Aleman P A, Ulrich K, Guijarro-García M, et al. Does talent management matter? Talent management and the creation of competitive and sustainable entrepreneurship models[J]. International Entrepreneurship and Management Journal, 2023, 19(3): 1055-1068.

[9]Kafetzopoulos D. Talent development: a driver for strategic flexibility, innovativeness and financial performance[J]. EuroMed Journal of Business, 2023, 18(2): 296-312.

[10]Sigala M, Ren L, Li Z, et al. Talent management in hospitality during the COVID-19 pandemic in Macao: a contingency approach[J]. International Journal of Contemporary Hospitality Management, 2023, 35(8): 2773-2792.

[11]Ganiyu I O, Atiku S O, Van der Byl K. An evolution of virtual training: implications for talent development in the post-pandemic period[J]. Development and Learning in Organizations: An International Journal, 2023, 37(2): 10-13.