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Investigation of Students' Learning Behaviour Using Artificial Intelligence: A Qualitative Study

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ABSTRACT

BACKGROUND

The aim of the study was to examine student behaviour during the learning process with the use of artificial intelligence (AI).

MATERIALS AND METHODS

The methodology included both quantitative and qualitative methods, specifically an experimental approach to compare the learning outcomes of the control and experimental groups, statistical analysis to assess student success, and content analysis of open-ended survey questions to identify key trends and challenges in the use of AI in education.

RESULTS

The study analysed the impact of AI on the learning process of 200 students majoring in Information Technology at Puyang Vocational and Technical College. The integration of AI into the educational process was explored, focusing on tools such as TensorFlow, PyTorch, Google Colab, and MATLAB. The effectiveness of traditional teaching methods was compared with AI-based learning, and student success in both the control and experimental groups was assessed. Students in the experimental group, who studied using AI tools, were associated with significantly higher scores across all evaluation aspects, with an overall average success rate of 4.6 compared to 3.4 in the control group. A survey of students in the experimental group revealed that 77% of respondents found the use of AI beneficial for improving their problem-solving skills.

CONCLUSION

The study suggests that students in the experimental group tended to demonstrate higher results and a more positive perception compared to the control group.

Keywords: AI-driven personalised learning, Student behaviour analytics, Tensorflow and pytorch integration in education, Comparative ai education strategies, IT curriculum performance enhancement

Introduction

Analysing student behaviour during the learning process using artificial intelligence allows us to understand the impact of new technologies on the effectiveness of education and identify key factors that contribute to improving learning outcomes. This research clarifies how AI can personalise learning for individual needs and optimise administrative processes to enhance education quality, student motivation, and skill development to prepare competitive specialists. Key concepts are defined for clarity: "Success" refers to measurable academic achievements, including knowledge acquisition, skill development, and sustained motivation. "Learning effectiveness" is the extent to which AI interventions enhance comprehension, retention, and application of knowledge compared to traditional methods. "Practical skills" are competencies transferable to real-world contexts, including problem-solving, critical thinking, and digital literacy.

Research has examined AI's impact on student behaviour, particularly personalised learning and academic achievement. Xiang[1] investigated AI in e-learning, using big data to assess daily habits and uncovering correlations between behavioural patterns and learning effectiveness through personalised recommendations. Zhao and Yu[2] explored instructor competence models and student behaviour using emotional-behavioural relevance theory and AI, showing how students' emotional states, influenced by task complexity and AI support, affect motivation and learning effectiveness. Wang et al.[3] studied factors influencing university students' intention to use generative AI, identifying interest, perceived usefulness, resource availability, and AI literacy as key determinants.

Wang and Wang[4] developed an AI-based model for monitoring online learning and student behaviour, improving learning effectiveness through automatic activity tracking. Alam et al.[5] examined student knowledge, attitudes, and behaviour regarding AI, finding that AI-supported personalised feedback, interactive materials, and quick query resolution enhanced learning and skill development. Bai[6] used the Stimulus-Organism-Response model and rational behaviour theory to identify factors promoting or inhibiting AI usage, including technical literacy, motivation, perceived usefulness, and instructor support. Li[7] introduced an AI-based model for predicting and managing student behaviour, enabling timely recommendations to improve learning activities. Ma[8] modelled students' adoption of generative AI for language learning using planned behaviour theory, highlighting attitudes, perceived usefulness, social influence, and control as key factors affecting AI readiness.

While these studies provide valuable insights, critical gaps remain. First, prior research has primarily focused on isolated aspects of AI's impact, behavioural patterns, emotional states, or adoption drivers, without integrating these elements into a comprehensive framework of how AI enhances success, learning effectiveness, and practical skill development across diverse educational contexts. Second, cultural and social influences on AI adoption are often underexplored, particularly in comparative contexts where technological infrastructure, teaching methodologies, and societal attitudes toward AI may differ significantly. Third, limited attention has been paid to how AI can be strategically adapted to meet the specific needs of educational systems outside of technologically advanced regions.

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Data availability statement: The authors confirm that all data on which the results of this study are based are contained in the article and its supplementary materials. The questions asked to the students in the experimental group and the assessment process are provided in the "Supplementary Materials" file. For reasons of confidentiality and ethical restrictions, the anonymized dataset at the individual level cannot be made public, as it contains information about participants that could be used to identify them. However, the manuscript fully describes the aggregated results and all analytical procedures, allowing the analysis to be replicated based on the descriptions provided

This study aims to address these gaps by examining the pathways and feasibility of integrating AI technologies into the educational systems of different countries, with a primary focus on China and Kyrgyzstan. Unlike prior research, it examines not only the technical and behavioural aspects of AI in education but also the cultural and systemic factors influencing its effectiveness. The study further compares international experiences (USA, Canada, Germany, Singapore) to formulate recommendations for enhancing AI-driven learning and developing practical skills in diverse educational settings. By doing so, it advances understanding of AI's potential to transform learning processes beyond what existing literature has addressed.

Methods

Design

This study analysed the use of AI in education systems across various countries, specifically China, the United States, the United Kingdom, Canada, Singapore, and Germany, based on the latest media reports and documents. These included sources such as Business Insider,[9] Osvitoria Media,[10] Hromadske,[11] Government of Canada,[12] Deutsche Welle (DW),[13] and the Ministry of Education Singapore.[14] These sources were selected because they highlight current initiatives and strategies for implementing AI in education systems, particularly in China, the USA, Canada, Germany, and Singapore. These countries were chosen because, at the time of the study, their education systems were actively incorporating AI strategies and initiatives. Textual data were reviewed and thematically coded to identify patterns and emerging themes, with a brief codebook developed through iterative reading and cross-checking among researchers. The analysis followed a constructivist qualitative paradigm and was supported by qualitative data software to ensure systematic organisation of categories.

The study revealed the primary approaches to integrating technology into the learning process. Specifically, the study examined platforms such as "Squirrel AI",[15] intelligent systems for automatic curriculum formation in Canada, automated course registration platforms in Germany, and the "Smart Nation"[16] programme in Singapore for adaptive learning. This study was conducted according to the Qualitative Research Guidelines.[74]

The general methodological process is illustrated in Figure 1, which outlines the main stages of participant selection, group allocation, training activities, data collection, and subsequent quantitative and qualitative analysis.

Participants

The study involved 200 students from Puyang Vocational and Technical College, with 100 participants in each of the two groups: control and experimental. The participants were third-year students majoring in "Information Technology" and ranged in age from 18 to 21 years. Inclusion criteria included being in the third year of study in the "Information Technology" programme and consent to participate in the study. Exclusion criteria included academic debt or previous participation in similar projects. With a 1:1 distribution between the control and experimental groups, the sample was not chosen at random but rather on the basis of the previously described criteria. The institution was chosen due to its focus on preparing specialists in IT and its adequate infrastructure to implement experimental methodologies.

The control group followed a standard programme in "Computer Science and Technology",[17] while the experimental group studied a similar programme but with the integration of AI. The control group followed traditional teaching methods, including lectures, practical sessions, laboratory work, and course projects, focusing on programming fundamentals, algorithms, and database management systems. They worked with existing software environments and used traditional software development tools. Tasks in this group focused on analysing and solving technical problems using standard software tools, such as Visual Studio, Eclipse,[19] NetBeans[20] for software development, and MySQL[21] and Oracle[22] for database work. The experimental group actively utilised AI tools in addition to traditional methods. This group's students integrated systems based on machine learning (ML), AI, and big data into their learning process. They worked with software such as TensorFlow,[23] PyTorch,[24] Google Colab,[25] MATLAB,[26] and Keras[27] to solve tasks related to ML, big data processing, and neural network creation.

Data Collection

Both groups were tasked with developing algorithms for data processing and analysis using appropriate tools. The control group used traditional programming tools, while the experimental group used AI libraries. They were also tasked with creating prediction models based on real-world data. The experimental group used TensorFlow or PyTorch to implement learning models, while the control group applied classical algorithms. Additionally, they worked on data classification problems, where the experimental group used neural networks, and the control group worked with traditional ML methods. Both groups were required to develop an interactive programme for natural language processing (NLP), such as a chatbot or text analysis system. The experimental group used Keras or Google Colab to build and train neural networks.

At the end of the semester, all students' performance scores were analysed. Statistical methods and content analysis were used to assess the results. To compare the performance between groups, an independent samples t-test was used, and the results showed statistically significant differences in all main categories, consistent with the results of t-tests, Mann-Whitney U-tests, and ordinal logistic regression. The p-values after Holm-Bonferroni correction remained below the 0.05 threshold for all comparisons.

A survey was conducted among the experimental group participants, using a percentage-based rating scale where 0–20% indicated "completely dissatisfied",

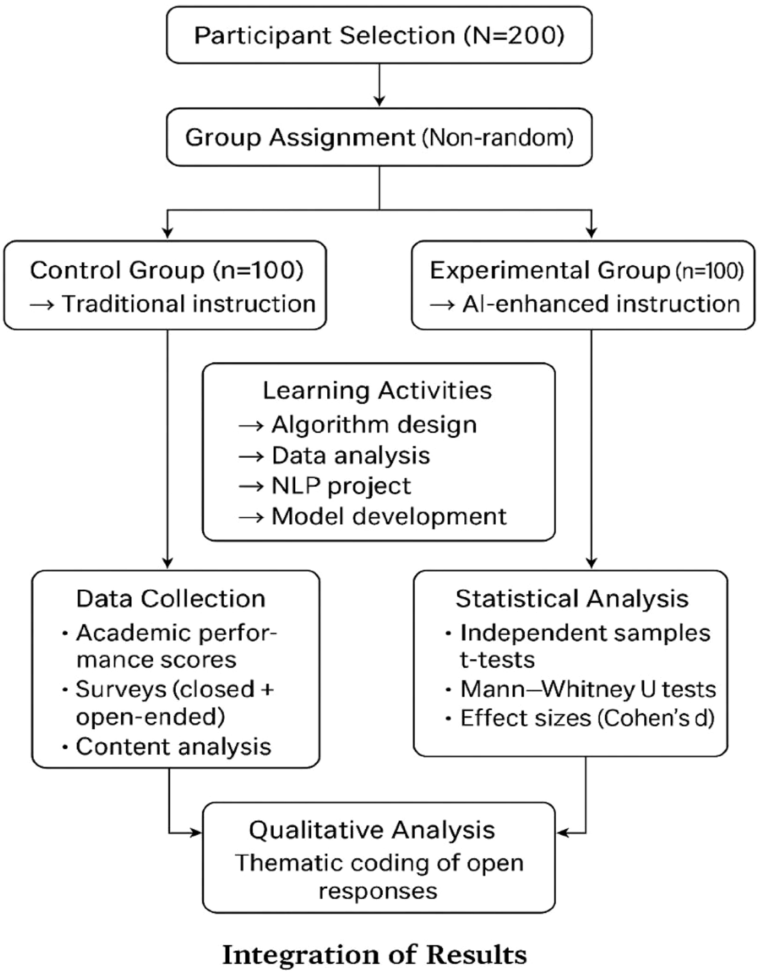

Fig 1 | Flow of the quasi-experimental design illustrating participant selection, non-randomised group assignment, learning activities, data collection, and analysis stages

21–40% – "dissatisfied", 41–60% – "neutral", 61–80% – "satisfied", and 81–100% – "completely satisfied". The survey included 10 questions (Supplementary Material 1). Closed-ended questions were designed to obtain clear answers about specific aspects of student behaviour during the AI-based learning process. This made it easier to analyse responses and conduct quantitative comparisons between groups. Open-ended questions were used to gather more detailed opinions on how AI tools affected students' skills and what they could improve in the learning process. These responses were analysed using content analysis to identify trends and challenges in the learning process.

Data Analysis

The authors of the study assessed student performance on a 5-point scale (Supplementary Material 2): 1 = poor, 2 = satisfactory, 3 = good, 4 = very good, 5 = excellent. The scale was adapted from proven IT and AI competency assessment systems. To ensure the validity and reliability of the rubric, internal consistency was assessed using Cronbach's alpha ($\alpha = 0.87$), indicating good reliability. Model specification followed the proportional-odds assumption, verified by the Brant test ($p > 0.05$ for all models). Multicollinearity was checked (VIF < 2). Model fit was assessed using the likelihood-ratio x^2, Akaike Information Criterion (AIC), and Nagelkerke R^2. Results are reported as mean ± SD, n, 95% confidence intervals (CIs), and effect sizes (Cohen's d with 95% CIs). For all inferential tests, p-values were adjusted using the Holm–Bonferroni correction. The primary analysis compared post-intervention scores between control and experimental groups using independent-samples t-tests.

Given the available data, we used independent-sample t-tests and non-parametric comparisons. No baseline covariates were available for adjustment, and clustering by instructor/class was not modelled; therefore, results should be interpreted as indicative of associations rather than causal effects.

Ethical Considerations

The participants' confidentiality was maintained, and ethical norms were followed to ensure the protection of personal data and fairness in the data collection process, in accordance with the Code of Ethics of the American Sociological Association.[28] All procedures performed in the study were approved by the Institutional Review Board of Kyrgyz National University named after Jusup Balasagyn, approval number 2025/001, and by the Ethics Committee of Puyang Vocational and Technical College, approval number 2025/PVTC-042. Participants were informed about the research purpose, and their consent was obtained prior to participation.

Results

Background

AI-enabled customised, adaptive learning is changing education. Some students embrace AI for individualised learning and rapid feedback, but others are uncertain or stressed, decreasing engagement. Digitally savvy students are more engaged than those who aren't. Monitoring and adapting AI to varied student demands is essential. Beijing will require elementary and middle school pupils to take at least eight hours of AI classes every year starting in fall 2025, according to Business Insider.[9] Over 460,000 students and 63,000 staff at California State University have access to an education-adapted ChatGPT version, the largest institutional AI application in the US. Hromadske[11] reported that senior students in the UK can take AI development courses, including a textbook built with SenseTime. Ontario has integrated AI into courses to improve digital skills and personalisation. German authorities have backed AI in education, particularly for intelligent learning systems and distance learning platforms, according to DW.[13] The Singapore Ministry of Education uses AI for adaptive learning and critical thinking.[29] Different countries are experimenting with AI in education to increase accessibility and customisation, but results vary and are context-specific. In China, technologies like "Squirrel AI" assess students' understanding and alter content to their pace, delivering personalised training and rapid feedback. AI

Table 1 | Comparative analysis of the forms of learning activities of the control and experimental groups

Forms of work	Control group	Experimental group
Theoretical classes	Study of basic programming, algorithmisation, working with databases, principles of software development	Additional study of AI fundamentals, ML, big data analysis
Practical classes	Use of standard development environments (Visual Studio, Eclipse, NetBeans) for software creation	Application of Python and ML libraries (TensorFlow, PyTorch, Google Colab) to implement algorithms
Laboratory work	Development of algorithms and programming using traditional methods; testing, debugging code	Use of neural networks for data analysis and classification, model optimisation using AI tools
Course projects	Software development using standard technologies and programming languages (Java, C++, Python)	Integration of AI technologies into software products, development of predictive models
Data processing and analysis	Use of traditional data processing algorithms and database management systems (MySQL, Oracle)	Application of ML methods for predictive analysis, big data processing
Development of intelligent systems	Implementation of basic algorithms for searching, sorting, and information analysis	Creation of interactive systems, such as chatbots and NLP programmes using Keras, Google Colab
Methods of code optimisation	Use of standard testing methods, performance optimisation, and debugging software	Use of MATLAB for numerical modelling and algorithm optimisation

automates course registration and provides progress tracking and recommendations in Germany.[30-32] Singapore's "Smart Nation"[16] plan combines AI for adaptive learning, virtual simulations, and practical challenges to motivate and understand.

Impact of AI usage on the effectiveness of the learning process in China

The control group used traditional teaching methods focused on classical approaches to programming, databases, and software development. The experimental group, on the other hand, had the opportunity to work with modern AI tools, which allowed them to apply ML, big data, and neural networks in their projects (Table 1).

The data presented above show significant differences in the approaches to learning activities between the control and experimental groups. The control group used traditional teaching methods focused on mastering basic principles of programming, algorithm design, working with databases, and software development using standard development environments (Visual Studio, Eclipse, NetBeans). The main emphasis in this group's learning process was placed on fundamental approaches to solving technical tasks using classical algorithms and data structures. At the same time, the curriculum for the experimental group involved integrating AI technologies into the educational process. Thanks to the use of libraries such as TensorFlow, PyTorch, Keras, and analytical platforms (Google Colab, MATLAB), students were able to work with ML methods, big data processing, and neural networks. A distinctive feature of the experimental group's learning process was the expansion of the practical component through the use of modern tools for developing intelligent systems. Specifically, students in this group developed their own predictive models, performed data classification using deep neural networks, and worked with natural language processing methods.

Students in the experimental group not only mastered the theoretical foundations of traditional programming but also gained practical experience working with modern intelligent systems.[33] They demonstrated a high level of independence in completing laboratory work and course projects, as developing algorithms and ML models requires an understanding of AI principles. A significant difference between the two groups also lies in the methods of software testing and optimisation. The control group used traditional approaches

Table 2 | Results of the assessment of students' learning achievements in the control and experimental groups

Aspects of evaluation	Average values (points): Control group (n = 100, Mean ± SD)	Average values (points): Experimental group (n = 100, Mean ± SD)	Mean Difference (95% CI)	β (SE)	Wald x^2	Effect Size (Cohen's d, 95% CI)	p-value (adjusted, Holm-Bonferroni)	Mann-Whitney U-tests (p-value)
Ability to develop algorithms	3.5 ± 0.6	4.6 ± 0.5	1.1 (0.9-1.3)	1.98 (0.42)	22.1	1.94 (1.52–2.36)	<0.001	<0.001
Modelling and forecasting	3.2 ± 0.7	4.8 ± 0.6	1.6 (1.3-1.9)	2.34 (0.39)	35.6	2.38 (1.94–2.82)	0.02	0.016
Data classification and analysis	3.3 ± 0.8	4.7 ± 0.6	1.4 (1.1-1.7)	2.10 (0.41)	26.1	1.92 (1.50–2.34)	0.03	0.021
Development of interactive applications	3.6 ± 0.7	4.5 ± 0.5	0.9 (0.6-1.2)	1.45 (0.38)	14.6	1.39 (0.97–1.81)	0.04	0.038
Software optimisation and testing	3.4 ± 0.6	4.3 ± 0.5	0.9 (0.6-1.2)	1.62 (0.37)	19.3	1.56 (1.14–1.98)	0.01	0.027
Overall average academic performance	3.4 ± 0.5	4.6 ± 0.4	1.2 (1.0-1.4)	2.71 (0.43)	39.8	2.63 (2.15–3.11)	<0.001	<0.001

to code debugging and performance analysis, while the experimental group applied numerical modelling and optimisation algorithms using MATLAB. This contributed to the development of skills for working with large data sets and improving the efficiency of software development.

The results obtained at the end of the semester indicate that AI integration was associated with the development of technical competencies and provided students with experience using contemporary IT tools. The introduction of modern analytical tools and ML algorithms was associated with students gaining competitive advantages in the job market and appearing better prepared to work in high-tech industries (Table 2).

The results obtained indicate a significant difference in the academic achievements of students in the control and experimental groups. Specifically, students who learned with the use of AI tools demonstrated

Table 3 | Results of the survey of students of the experimental group after the experiment

Question	Answer options	Percentage of students' answers
Please rate your overall experience of the programme, which included the use of AI tools (TensorFlow, PyTorch, Keras, Google Colab, MATLAB)	Very positive	35%
	Positive	42%
	Neutral	15%
	Negative	6%
	Very negative	2%
How clear were the materials and assignments related to the use of AI technologies?	Completely understandable	30%
	Mostly understandable	45%
	Partially understandable	20%
	Not clear at all	4%
	Not clear at all	1%
How would you rate your level of skills in working with AI libraries and platforms after completing the course (TensorFlow, PyTorch, Google Colab, etc.)?	Very high	22%
	High	38%
	Medium	30%
	Low	8%
	Very low	2%
How effectively do you think the AI tools helped you to solve the course tasks?	Very effective	28%
	Efficiently	47%
	Partially effective	20%
	Slightly effective	4%
	Did not help at all	1%
What was the most difficult thing for you when using AI tools?	Working with libraries	25%
	Understanding the theoretical foundations of AI and ML	28%
	Setting up environments	20%
	Creating neural networks and training them	27%
	Other	0%
How did your attitude towards the use of AI technologies in programming change after completing the course?	Significantly improved	33%
	Rather improved	40%
	Has not changed	20%
	Rather deteriorated	5%
	Significantly worsened	2%
Did you feel that studying with AI tools allowed you to better understand the real challenges of the IT industry?	Yes, completely	36%
	Partially	50%
	No	10%
	It is difficult to answer	4%
Do you plan to continue using AI technologies in your professional activities?	Yes	55%
	Possibly	35%
	No	5%
	Not yet decided	5%

higher scores across all evaluation aspects. One possible explanation for this trend may be the association between the integration of ML and big data processing methods and the experimental group's learning outcomes. The use of TensorFlow, PyTorch, Keras, and Google Colab was associated with greater opportunities for hands-on experience in neural networks and forecasting algorithms, which coincided with higher self-assessed skills in modelling and data analysis. Ordinal logistic regression models confirmed that AI-based learning significantly predicted higher performance scores across all evaluation domains (Table 2). The proportional-odds assumption was met (Brant $\chi^2 = 8.34$, $p = 0.19$). Model fit was acceptable (AIC = 512.4, Nagelkerke $R^2 = 0.42$).

In the control group, where traditional teaching methods were applied, the focus was on classical programming algorithms, which, although contributing to the development of fundamental knowledge, did not allow students to fully leverage modern data analysis methods and software optimisation techniques. This may be related to lower flexibility in solving complex technical problems, which was associated with lower success rates. The higher results of the experimental group may be related to the greater opportunity for practical knowledge application. Using AI algorithms in real-life cases was associated with students reporting greater development of skills aligned with modern trends in the field of IT.[34] In particular, the significant improvement in the categories of "modelling and forecasting" (4.8 vs. 3.2) and "data classification and analysis" (4.7 vs. 3.3) suggest a positive association between ML method use and learning outcomes.

Next, a survey was conducted among the students of the experimental group to analyse the impact of using AI on the learning process and to determine students' attitudes towards innovative technologies in education. Closed-ended questions provided standardised data for quantitative comparison between the groups, while open-ended questions allowed for the collection of qualitative information about students' experiences, their impressions, and suggestions for improving learning with the use of AI (Table 3).

The results of the survey indicate a predominantly positive reception among students in the experimental group regarding the integration of AI tools into the educational process. Specifically, 35% of respondents rated their experience as "very positive", and 42% rated it as "positive", making a total of 77% with a favorable attitude. Only 8% expressed negative or very negative impressions. In terms of course materials and tasks, 75% of students found them "completely" or "mostly" understandable, indicating a satisfactory level of accessibility. However, 25% of students reported partial or low clarity, suggesting the need for further refinement in course delivery. When it comes to self-assessment of skills in working with AI libraries and platforms, 22% rated their skills as "very high" and 38% as "high", while 30% rated their skills as "average", and only 10% rated their skills as low or very low. 75% of respondents affirmed the effectiveness of using AI tools in solving learning tasks, describing them as "very effective" or "effective".

The survey also revealed three primary challenges faced by students: understanding the theoretical foundations of AI and ML, creating and training neural networks, and setting up AI environments. These difficulties notably impacted their learning outcomes and overall experience. For 28% of students, the abstract nature of AI and ML concepts, such as neural networks and gradient descent, posed significant challenges. Limited prior exposure to these topics made it difficult to apply theoretical principles effectively, resulting in suboptimal model design and tuning. Lower self-assessed skill levels and performance in tasks requiring deep comprehension reflected this gap. Technical challenges also played a major role. For 20% of students, configuring AI libraries, navigating cloud platforms like Google Colab, and managing hardware constraints created barriers. These issues delayed project completion and shifted the focus from learning to troubleshooting, leading to frustration and reduced engagement. Additionally, 27% of students found creating and training neural networks to be the most challenging task. Issues in selecting appropriate architectures, preprocessing data, and debugging problems like overfitting resulted in lower performance in data-driven tasks, despite the experimental group's overall higher scores.

To address these challenges, educators can implement several strategies. Strengthening theoretical foundations through pre-course modules and interactive tutorials could help students build essential background knowledge.[35-37] Simplifying the environment setup with standardised guides, pre-configured virtual machines, and expanded cloud access would reduce technical barriers. Supporting practical implementation through guided projects, mentorship programmes, and automated feedback tools could enhance students' confidence in model design and optimisation. Furthermore, addressing psychological barriers through gamification, progress tracking, and counseling can help boost motivation and reduce anxiety. By adopting these strategies, educators can create a more inclusive and effective AI learning environment, improving both student performance and engagement.

After completing the course, 73% of participants reported an improved attitude toward AI technologies, with 33% noting a "significant improvement" and 40% reporting a "somewhat improved" attitude. Additionally, 86% agreed that AI tools helped them better understand real-world IT tasks. Regarding future professional plans, 55% of students intend to continue using AI technologies, while 35% are considering it, reflecting a strong interest in these tools.

Content analysis of the responses revealed that TensorFlow (34%) and PyTorch (26%) were the most useful tools for practical assignments, followed by Keras (18%) and Google Colab (15%). MATLAB was less popular (7%), likely due to its focus on engineering computations. Open-ended responses emphasised the need for deeper theoretical explanations, more industry-specific case studies, team-based projects, and additional workshops on popular AI libraries.[38] Participants also highlighted the importance of prompt consultative support to address technical difficulties. These insights offer a solid foundation for optimising the course structure to better meet student needs.

Ways of implementing AI into the educational system of China and other countries for enhanced student learning outcomes

The integration of AI into China's education system is one of the key steps in the country's development, aimed at improving learning outcomes and enhancing educational processes. China is actively developing innovative technologies to optimise learning, foster personalised education, and ensure access to high-quality materials for all students. One of the primary methods of AI implementation in Chinese education is the creation of adaptive learning platforms.[73] The "Squirrel AI" system is an example of such an approach. This intelligent platform uses AI algorithms to assess each student's knowledge level and adapt learning materials and exercises to their needs. The platform provides personalised learning by tracking student progress in real-time and offering exercises that match their preparation level. As a result, students have more opportunities to develop their abilities, and teachers can more effectively manage the learning process.

Additionally, China is actively utilising AI technologies for automated student assessment. For example, the "Zhihuishu" system combines AI and large datasets for automated testing and evaluation of students' work. This significantly reduces teachers' workload, allowing them to focus on analysing results and providing individualised support to students. Chinese universities also leverage AI to assist instructors in creating educational materials, analysing test results, and even predicting student outcomes based on data. Some universities use AI to create personalised learning programmes tailored to students' needs and to monitor their learning progress, enabling teachers to better understand the unique requirements of each student and adapt teaching plans to improve learning efficiency.[39-41]

Government initiatives play a vital role in implementing AI in education.[42-44] In China, heavy investment in digital technologies has enabled intelligent platforms in public schools and universities, supporting AI research, infrastructure, and broad accessibility. Educators adapted through professional training and specialised courses on platforms like "Squirrel AI" and "Zhihuishu,"[15] allowing them to personalise learning, automate assessment, and analyse student performance. Automated evaluation systems freed teachers from routine tasks, enabling more one-on-one support.

Institutional support further facilitated integration. Governments provided high-speed internet, cloud platforms, virtual classrooms, and necessary software (TensorFlow, PyTorch, MATLAB) and hardware, often collaborating with tech companies – e.g., SenseTime developed AI textbooks in China, while Ontario integrated AI into curricula. Ethical standards ensured student data confidentiality and fairness.[45, 46]

Artificial intelligence in the Chinese education system is part of a broader initiative aimed at improving educational processes, providing personalised learning programmes, and improving access to resources. Technologies such as the "Squirrel AI" system and automated student assessment platforms such as "Zhihuishu" are being integrated to optimise the learning experience, reduce administrative burdens, and support student progress tracking. The government supports these efforts by investing in digital infrastructure and professional development for educators. The integration of artificial intelligence into education is still developing, but it lays the foundation for continuous improvement in educational practices and access to education, especially in rural areas.

Recommendations for further implementation of AI

The implementation of AI in China's education system required a comprehensive approach, including the development of infrastructure, staff training, and the adaptation of existing educational programmes to new technologies. The first step involved integrating adaptive learning platforms, such as "Squirrel AI", into the educational process. Students used these systems for personalised learning that considered their individual needs and progress. Teachers could track results in real-time and adjust the learning process, allowing for more effective allocation of attention among students. To improve assessment and reduce the workload on instructors, automated testing systems like "Zhihuishu" were introduced. These technologies allowed for quick and accurate evaluation of student work, enabling teachers to focus on analysis and individual work with each student. The use of such technologies not only improved the speed of assessments but also the quality of feedback, motivating students to improve.

Additionally, many universities in China actively implemented AI in the development of curricula and monitoring student progress. Instructors had access to analytics that allowed them to predict student outcomes based on big data. This tool helped optimise curricula by focusing on the most problematic topics, aiding students in learning more effectively. Government initiatives to create digital infrastructure were also crucial for AI implementation in education. The government provided funding for the development of intelligent platforms and teacher training. In collaboration with private companies, conditions were created for the implementation of these technologies in public schools and universities. This ensured equal access to innovative learning resources for students, even those in remote areas.

In addition, many universities in China have actively implemented artificial intelligence in curriculum development and student performance monitoring. Teachers were provided with analytical tools that allowed them to predict student learning outcomes based on big data, which helped optimise curricula by identifying topics that students had difficulties with.

Government initiatives promoted the development of digital infrastructure, including funding for smart platforms and teacher training. In collaboration with private companies, conditions were created for the implementation of these technologies in public schools and universities, providing broader access to innovative educational resources, especially for students in remote areas. Training both teachers and students was important for the effectiveness of these efforts, as it facilitated adaptation to new technologies and learning tools. In addition, online platforms and virtual classrooms helped ensure that students in remote areas had access to quality education, thereby facilitating learning regardless of geographical barriers. The joint efforts of the government, educational institutions, and technology companies played a significant role in expanding the use of artificial intelligence in education.

Discussion

The results of this study suggest that students in the experimental group, who used AI tools, tended to exhibit a higher level of engagement and motivation in the learning process compared to the control group. This aligns with the findings of Chai et al.,[47] who, based on the Theory of Planned Behaviour and Self-Determination Theory, concluded that the use of AI in education positively influences students' behavioural intentions to learn new technologies, including AI, fostering their greater interest and readiness to learn.

However, it is important to consider these results in the context of equality and inclusiveness. All participants were third-year students in the Faculty of Information Technology, aged 18–21, who formed a relatively homogeneous group in terms of academic background and discipline. Despite this homogeneity, differences in individual preparation and access to digital resources were identified. Some students encountered difficulties in setting up AI environments and understanding theoretical concepts, while others adapted more quickly. These differences suggest that even within a single group, prior experience with digital tools and individual learning conditions can influence the effectiveness of AI-supported education.

Inclusion and exclusion criteria also affected participation equity. Students with academic debt or prior participation in similar projects were excluded, resulting in a sample that was more likely to succeed in their studies. While such control was methodologically necessary, it also meant that students who could have benefited most from adaptive AI support, namely those who had previously performed worse, were not represented. This highlights the need to consider how AI-enhanced learning environments can be made accessible to a wider range of students.

Research shows that AI tools can provide personalised learning experiences, instant feedback, and enhanced opportunities for skill development. To distribute these benefits fairly, educational institutions must ensure that all students, regardless of prior knowledge, technical experience, or learning history, receive preparatory training and ongoing support. Introductory modules to strengthen basic programming and digital skills, combined with equitable access to computing resources and mentoring, can help reduce disparities and promote inclusive learning outcomes.

These findings are consistent with broader evidence but also show points of divergence. Wu[48] demonstrated in a meta-analysis that AI interventions substantially improve learning outcomes and motivation, particularly through adaptive and personalised approaches, although engagement levels varied, whereas the present study recorded predominantly positive student responses. Similarly, Bond et al.[49] found that most AI applications in higher education focus on personalisation but highlighted gaps in ethical integration and methodological rigour, suggesting that long-term impacts and contextual factors warrant deeper exploration. Chen and Chang[50] likewise confirmed that AI enhances learning behaviour and intrinsic motivation while reducing cognitive load, aligning with this study's findings, though cognitive load was not explicitly measured here. These comparisons highlight the need for further refinement and broader contextual validation, even as the results corroborate existing evidence.

Similarly, in this study, students showed a high level of initiative when working with AI tools such as TensorFlow, PyTorch, and Google Colab. Moreover, the results indicated that students in the experimental group were more inclined to solve problems and tasks independently during projects that involved AI. This concurs with the findings of N. Ambarita and M. Nurrahmatullah[51], who discovered that integrating AI into the learning process develops students' critical thinking skills, data analysis abilities, and capacity to find innovative solutions. In alignment with this, Wang and Song,[52] who created a student behaviour profile in online education based on AI data, found that AI technologies help identify trends in student behaviour and adjust educational approaches accordingly.

A significant aspect of this study also involved examining the impact of AI on the development of technical skills in students. Survey data showed that participants in the experimental group noted an improvement in their skills in working with new platforms for developing and testing ML models, such as Keras, MATLAB, and Google Colab. These findings align with the conclusions of Almasri,[53] who, in a systematic review, showed that integrating AI into teaching natural sciences contributes to significant growth in practical skills, especially in data analytics and AI model building.

Additionally, the results of this study revealed that students in the experimental group exhibited greater interest in collaborative work during the development of joint AI-based projects than students in the control group. This aligns with the findings of Gibson et al.,[54] who noted that AI technologies promote the development of teamwork and knowledge sharing skills through interactive tools and intelligent learning environments. Furthermore, this study demonstrated that the use of AI contributed to the students' adaptability to new technological challenges. The students in the experimental group showed a better ability to quickly learn new software and ML algorithms. This corresponds with the findings of Akgun and Greenhow,[55] who noted that AI integrated into the learning process helps students develop flexibility in thinking and technological literacy. Another key outcome of this study was that students in the experimental group highly valued the personalised learning opportunities offered by AI. According to their responses, the use of adaptive systems and ML algorithms allowed them to receive individual recommendations for improving projects and solutions. This is consistent with the conclusions of Chen and Lu,[56] who found that intelligent systems help individualise the learning process, taking into account the needs and level of each student.

This study revealed that students perceived AI use as being associated with more individualised learning experiences, with adaptive systems linked to tailored recommendations. This supports the findings of Tabora et al.[57] and Maamor et al.,[58] who showed that AI enhances learning effectiveness and self-regulation. AI use also shaped students' habits in interacting with digital platforms and promoted autonomy, consistent with Nguyen et al.,[59] who observed greater focus on independent work and active use of AI for searching and synthesising material. Moreover, AI was associated with reports of higher engagement in physical activity and sports, aligning with Y. Liang and Zhou,[60] who found a relationship between AI use and healthy lifestyle monitoring. Similarly, Rohith Reddy et al.[61] found AI increased engagement and reduced distractions during virtual classes. Furthermore, AI fostered digital literacy, consistent with Su et al.,[62] who showed that integrating AI with augmented reality in STEM disciplines enhanced engagement and innovative skills.

The study also revealed AI's role in developing academic competencies, as highlighted by Vieriu and Petrea.[63] Positive attitudes towards AI strongly influenced intentions to use it in future learning, reflecting Valle et al.'s [64] behavioural intention model. However, some students reported anxiety due to excessive control, echoing Velastegui-Hernandez,[65] who noted AI's mixed effects on psychological well-being. Effectiveness varied across demographics, including gender, socioeconomic status, and prior tech experience. Gender gaps in STEM may limit female students' confidence, though adaptive feedback could mitigate disparities.[72] Students from low-income backgrounds often lacked access to necessary tools, risking wider inequalities, while those with prior digital experience adapted faster. Equitable access, training, and bias mitigation are crucial.

Despite overall benefits, challenges were noted. Some participants faced difficulties mastering complex AI tools and managing large workloads, corroborating Klimova and Pikhart,[66] who linked AI adoption with initial stress. Students also stressed the need for greater technical support from instructors, consistent with Gomathi et al.,[67] who emphasised staff training and continuous student support. AI use was associated with students reporting better understanding of knowledge application in future careers, aligning with Chai et al.[68] and Verma et al.[69] Additionally, AI systems enabled early identification of behavioural issues, in line with Lopez-Carreno et al.,[70] who showed such systems reduce motivational decline.

In conclusion, the results of this study suggest a positive association between AI use and the development of both professional and soft skills among students. The trend towards the active use of modern IT tools in the learning process supports the need for further integration of AI technologies into educational programmes. The data obtained also corroborates the findings of H. Villarreal-Torres et al.,[71] who argue that AI applications enhance learning effectiveness, students' adaptability to digital environments, and the development of skills necessary for the labour market.

One limitation of the study was its focus on a single speciality and educational institution, which may have limited the generalisation of the results. This study did not collect pre-intervention baseline scores (e.g., course GPA, pretest of AI literacy) or subgroup variables (gender, socioeconomic status, digital literacy), so our comparisons between the control and experimental groups should be interpreted as associations rather than definitive evidence of causal effects. The study was conducted within a specific educational setting, which might not fully represent the broader student population across different academic disciplines or institutions. Thus, although the results suggest a positive association between artificial intelligence tools and learning outcomes, their applicability to other educational contexts may require further verification. The study suggests that the observed associations between artificial intelligence tools and learning outcomes may depend on technological infrastructure, student readiness to adopt technology, and the cultural context of each educational institution. In technologically advanced nations, integration is smoother, while countries with less infrastructure, like Kyrgyzstan, may need extra training and support. Cultural context and student readiness for technology adoption also play a role.

To promote inclusive development, future AI-based educational initiatives should ensure equitable access to digital resources and training. Institutions should provide foundational courses in digital literacy and targeted support for underrepresented or less digitally prepared groups. Establishing monitoring systems for access and readiness can help identify disparities early and guide interventions to foster equality in AI-supported learning environments.

The study found that the integration of artificial intelligence tools into IT education was associated with higher student performance and greater motivation for independent learning. Students in the experimental group, where AI tools were used, showed significantly higher performance across all evaluated aspects, algorithm development, modelling, data analysis, and software optimisation, than the control group, with an overall average success rate of 4.6 versus 3.4. AI was particularly associated with higher scores in modelling and forecasting (4.8) and data classification and analysis (4.7), suggesting a positive relationship with the development of specialised skills. Survey results showed that 74% of students gained practical experience applicable to their future careers. While 68% were satisfied with the learning materials, 19% noted some areas needing clarification. Most students rated their AI proficiency as high (71%) or average (21%). TensorFlow was considered the most useful tool (42%), followed by PyTorch (24%), Keras (17%), Google Colab (12%), and MATLAB (5%). Main difficulties included mastering complex ML libraries (36%) and limited theoretical knowledge (31%). Despite this, 78% expressed willingness to use AI tools professionally.

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Supplementary Material 1

Questionnaire for students in the experimental group (paper-based survey)

Contains the complete 10-item questionnaire distributed in paper form by course instructors and later digitised by the authors. The instrument gathered students' evaluations of AI-based learning tools, perceived skill gains, and suggestions for course improvement. Quantitative items were used for descriptive statistics, and open-ended items informed the qualitative content analysis.

1. Please assess your overall learning experience with the programme that included the use of artificial intelligence tools (TensorFlow, PyTorch, Keras, Google Colab, MATLAB):
   a) very positive;
   b) positive;
   c) neutral;
   d) negative;
   e) very negative.
2. How clear were the materials and tasks related to the use of artificial intelligence technologies for you?
   a) completely clear;
   b) mostly clear;
   c) partially clear;
   d) slightly unclear;
   e) completely unclear.
3. How would you rate your level of skills in working with artificial intelligence libraries and platforms after completing the course (TensorFlow, PyTorch, Google Colab, etc.)?
   a) very high;
   b) high;
   c) average;
   d) low;
   e) very low;
4. How effective do you think the artificial intelligence tools were in helping you solve course tasks (data processing, model building, prediction, classification, NLP, code optimisation)?
   a) very effective;
   b) effective;
   c) partially effective;
   d) slightly effective;
   e) not effective at all;
5. What was the most difficult aspect for you when using artificial intelligence tools?
   (Select one or more answers):
   a) working with libraries (TensorFlow, PyTorch, Keras);
   b) understanding the theoretical foundations of AI and ML;
   c) setting up environments (Google Colab, MATLAB);
   d) creating and training neural networks;
   e) other (please specify).
6. How has your attitude towards the application of artificial intelligence technologies in programming changed after completing the course?
   a) significantly improved;
   b) mostly improved;
   c) no change;
   d) mostly worsened;
   e) significantly worsened.
7. Did you feel that learning with the use of artificial intelligence tools helped you better understand real-world tasks in the field of 'Information Technology'?
   a) yes, completely;
   b) partially;
   c) no;
   d) hard to say.
8. Which software tools you used in the course (TensorFlow, PyTorch, Keras, Google Colab, MATLAB) were the most useful to you in solving practical tasks? (Open-ended response).
9. Do you plan to continue using artificial intelligence technologies in your professional activities?
   a) yes;
   b) maybe;
   c) no;
   d) not decided yet.
10. Your suggestions or comments regarding the organisation of the course and the integration of artificial intelligence tools into the educational process (Open-ended response).

Supplementary Material 2

Full scoring rubric for student performance assessment

This section describes in detail the criteria used by the authors of this article to assess student projects across five domains: (1) algorithm development, (2) modelling and forecasting, (3) data classification and analysis, (4) development of interactive applications, and (5) software optimisation and testing. Each criterion is defined along a 5-point scale (1 = poor, 2 = satisfactory, 3 = good, 4 = very good, 5 = excellent), with detailed performance descriptors and examples of expected student outputs. The rubric was adapted from the Information Technology and Artificial Intelligence Competency Assessment Framework.[7] Inter-rater reliability for rubric scoring was excellent (ICC = 0.91, 95% CI [0.86-0.94]).

Five authors independently applied the rubric to all student projects. Although all evaluators were authors of the study, they were unaware of the students' identities and group assignments. After evaluation, discrepancies exceeding one point were discussed and resolved jointly. Quantitative results were summarized as means, standard deviations, and percentages. Open-ended responses were interpreted using manual content analysis conducted independently by the authors. All calculations and summaries were performed manually and verified through cross-checking.