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The impact of student number and class duration on the effectiveness of artificial intelligence-assisted learning

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ABSTRACT

The aim of this study is to determine the effects of class size and course duration on students' academic performance in artificial intelligence (AI)-supported learning environments and to develop recommendations for optimizing these parameters. Previous research has not examined the simultaneous impact of class size and course duration on the effectiveness of AI-assisted learning. To achieve this objective, a quasi-experimental design was employed, including a control group (CG) (n=75) and an experimental group (EG) (n=20). Outcomes were assessed using pre-test and post-test measures evaluating knowledge of Chinese history. Statistical hypotheses were tested using independent samples t-tests and one-way analysis of variance (ANOVA). The EG demonstrated a significantly higher mean post-test score (85.6) compared to the CG (76.3), with statistical significance at p<0.05. The effect size (Cohen's d) was approximately 1.65, indicating a high level of practical significance. The findings provide a foundation for developing targeted strategies to integrate AI into higher education.

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1. INTRODUCTION

Social media is increasingly used by many higher education teachers and students for personal and educational purposes [1]. The development of digital technology has undergone a significant acceleration in recent decades, and the changes this technology has brought to social life have determined the need for an innovative approach to learning [2]–[4]. Educational institutions face challenges arising not only from technological progress, but also from the extraordinary circumstances caused by the COVID-19 pandemic [3], [5]. Forced to switch to distance learning, teachers and students found that traditional teaching methods were less effective [2], [6]. Artificial intelligence (AI) acts as a promising and innovative educational technology that changes the learning paradigm and contributes to the individualization of the educational process [7].

The development of educational computers and computer networks in the late twentieth and early twenty-first centuries exacerbated pedagogical divergences. New learning theories based on constructivist epistemology emerged and emphasized the role of technology in augmenting rather than replacing human intelligence [8]. In light of these transformations, the effectiveness of learning with the use of AI is defined as one of the most urgent problems. This is recognized both by experts in the field of education and representatives of the labor market, who require graduates to not only have deep knowledge, but also be able to work with innovative technologies [9], [10]. AI technology is based on the ability of programs and algorithms to perform tasks that were traditionally considered a privilege of the human intellect [7], [10]. With the development of computing and information processing technologies, AI has been widely used in educational practice (AI in education or AIEd), for example, intelligent learning systems, educational robots, learning analytics information panels, adaptive learning systems, human-computer interaction [10], [11]. Since AIEd's debut almost three decades ago, AI has been recognized as a powerful tool to foster new paradigms in instructional design, technological development, and educational research that cannot otherwise be developed within traditional education settings [12]–[14].

Although AI has the potential to transform education [13], high-quality learning outcomes are rarely achieved solely through advanced AI computing technologies [15], [16]. Therefore, the investigation of the impact of student number and class duration on learning effectiveness has become the object of extensive scientific research in the context of the application of innovative technologies in higher education [3], [17]–[19]. This article is devoted to the study of the impact of two main factors-student number and class duration-on the quality and effectiveness of the AI-based educational process. The purpose of the study is to identify the possibilities of optimizing these parameters to achieve the highest quality standards of higher education. Considering the great importance of this problem and its reflection in the challenges of today's education, this article seeks to shed light on the scientific and practical aspects of using AI to achieve optimal conditions for training future specialists.

Technology is neither helpful nor harmful to learning when used primarily as a means of presenting information (for example, when information is viewed on a computer screen rather than on paper). However, technology can be beneficial if it provides unique opportunities and effective learning principles [4]. Although technology is widely implemented in education, there is a lack of research on the effect these technologies can have on student learning and why such effects occur-a major research gap. The analysis of the literature on the impact of student number and class duration on the effectiveness of AI-assisted learning reveals a great deal of important trends and challenges that determine the relevance of the current study.

The implementation of AIEd had a significant impact, as evidenced by the increased efficiency of the educational process, the promotion of global learning, the personalization of learning, the creation of more intelligent content, and the optimization of education management efficiency [20], [21]. AI is emerging as a new technology with great potential in the field of education, as AI-based systems can facilitate personalized learning by adapting to the needs and interests of each student [14]. AI is used in education primarily for providing feedback and guidance to students, as well as for reducing educational costs [22]. From a biological and psychological perspective, AI-supported personalized learning aligns with mechanisms of neuroplasticity, as adaptive feedback and spaced repetition can strengthen synaptic connections associated with memory consolidation and skill acquisition [23].

The rapid development of computing and information processing technologies has accelerated the progress and application of AI, which enables computers to perform tasks by imitating human intellectual behavior, such as inference, analysis, and decision-making [24], [25]. Nowadays, AI is applied in various fields such as visual and voice recognition, decision making, natural language processing, and language translation in various forms such as computer programs, apps, embedded equipment control systems, or robots [26], [27]. For instance, some robots can interact with humans using visual and audio tracking technologies [28], while some medical systems can assist human experts in identifying potential diseases or making judgments by analyzing large data sets [29], [30].

The development of digital technologies in education is primarily interpreted as a gradual transition toward new norms of organizing the educational process, in which technological infrastructure assumes a systemic role [31]–[33]. Contemporary research highlights a conceptual shift that places AI at the center of this transformation. This shift entails not only instrumental modernization but also a profound reconsideration of pedagogical practices. In particular, it has been demonstrated that integrating AI through mechanisms such as adaptive personalization, predictive analytics, and individualized learning trajectories improves the quality of education [9], [34], [35]. However, this optimistic discourse conceals a range of conceptual and empirical contradictions that significantly complicate the interpretation of AI-assisted learning effectiveness. On the one hand, algorithm-driven personalization is often regarded as a universal means of enhancing learning outcomes. On the other hand, its practical implementation depends on a deep transformation of educational paradigms-a transformation that is not always supported at the institutional or methodological levels [22], [36], [37]. In this context, a tension emerges between the traditional role of the teacher as the primary agent of assessment and the expanding functional capacities of AI, which increasingly assume responsibilities related to monitoring and feedback. Uncertainty about the validity and fairness of algorithmic evaluation further intensifies this tension, which remains underexplored in prior research.

Moreover, the complexity of this issue is exacerbated by inconsistent findings regarding the impact of class size. Some studies provide compelling evidence that smaller class sizes are associated with higher academic achievement, improved long-term learning outcomes, and even enhanced career prospects [38].

Conversely, other empirical findings indicate minimal effects or a lack of statistical significance, thereby challenging the generalizability of this relationship. A similar duality is observed in the evaluation of overcrowded classrooms: although they are commonly perceived as limiting interaction, engagement, and attendance [39], certain studies emphasize the potential compensatory role of technological tools-particularly AI-which may partially offset the lack of individualized attention. Consequently, the contemporary academic discourse is characterized by fragmentation and the absence of a coherent theoretical and methodological framework for integrating the effects of key educational environment parameters, such as class size and lesson duration, within the context of AI-supported learning. Against this backdrop, the present study adopts a fundamentally different approach, moving beyond a descriptive analysis of individual factors and instead integrating them into a comprehensive analytical model.

The concept of the impact of AI on teaching effectiveness is fully integrated into a comprehensive analytical model. Within this model, AI operates not as an auxiliary tool but rather as a cognitive-communicative mediator that fundamentally reshapes the architecture of teacher interaction and, consequently, its specific characteristics [40]. This approach rejects linear, cause-and-effect interpretations in favor of a multifactorial, nonlinear, interdependent system. The proposed conceptual framework delineates three domains of analysis: the parametric characteristics of the learning environment (particularly group size and instructional duration), the modality of AI-mediated interaction, and the resulting learning outcomes. AI functions as an adaptive and regulatory agent capable of simultaneously calibrating the intensity, depth, and degree of personalization in instructional interaction [41].

Within this model, group size is treated as a structural parameter that determines the density of communication flows and the degree of individualized educational engagement. In larger groups, there is a tendency toward reduced personalized interaction, which is traditionally compensated by algorithmically generated feedback, predictive analysis of learning trajectories, and automated recommendations [42]. In contrast, in smaller groups, AI assumes a less compensatory and more intensifying role, enhancing the cognitive diversity of interactions and facilitating the development of analytical and reflective practices [38]. The temporal dimension of learning, represented by instructional duration, is conceptualized as a resource that determines the scope for engaging cognitive operations of varying complexity. In shorter sessions, AI tools function as mechanisms of cognitive compression, enabling more intensive learning through immediate feedback and optimized access to knowledge [38]. In longer instructional interactions, their role shifts toward supporting metacognitive regulation by facilitating processes of reflection, self-correction, and deeper understanding.

A central feature of this system is the multidimensional structure of interaction, encompassing cognitive, socio-communicative, and technological dimensions [40], [41]. The cognitive dimension reflects the level of intellectual information processing, the socio-communicative dimension captures the intensity and quality of intersubjective interaction, and the technological dimension represents the degree of AI integration into the educational process. It is through the transformation of these dimensions that AI exerts an indirect influence on learning outcomes. From this perspective, learning outcomes are multidimensional, encompassing cognitive achievements, metacognitive regulatory capacities, as well as affective and motivational states. Their emergence is determined not by the direct effect of AI, but by a complex network of interactions in which learning environment parameters function as moderators, while interaction characteristics act as mediators of the overall effect [7], [35].

The motivation for writing this research paper is based on the recognition of the key role of AI in the modern educational process and the need to study the impact of student number and class duration on the effectiveness of learning. The growing interest of teachers and students in the use of technology requires a thorough understanding of how the capabilities of AI interact with the structure and organization of the educational process. The hypothesis of the study is as: The use of AI in university education is effective, but its impact may depend on the number of students and class duration. The purpose of the study is to determine the impact of student number and class duration on the effectiveness of AI-assisted learning, as well as to develop recommendations for the optimal implementation of AI technologies in large and small student groups. The study has the following objectives:

- Implement AI technologies (i.e., ChatGPT) into the learning process in student groups of different sizes and class duration.
- Analyze the effectiveness of this implementation.
- Develop recommendations for teachers and educational institutions regarding the optimal use of AI.

2. METHOD

2.1. Study design

The study was designed as a quasi-experiment with a factorial structure to isolate and independently assess the effects of two key variables-group size and lesson duration-on academic performance. Students were divided into experimental group (EG) and control groups (CG). The EG was instructed in smaller groups with shorter sessions (60 minutes), whereas the CG studied in larger groups with longer sessions (90 minutes). For analytical precision, these parameters were treated as separate independent variables: i) group size (small vs. large) and ii) lesson duration (60 vs. 90 minutes). This design enabled the application of analysis of variance (ANOVA) to examine both the main effects of each factor and their interaction effects. The dependent variable was academic performance, measured by test scores in Chinese history (pre-test and post-test). In addition, learning gains were analyzed to provide a more accurate assessment of the educational intervention.

The implementation of AI was standardized across both groups. Students engaged with AI through text-based prompts that provided explanations of the learning material, clarification of concepts, illustrative examples, and responses to questions. The frequency of use was limited to three to five queries per session. The actual number of interactions was recorded and included as an additional variable in the regression analysis. The instructor structured the learning process, provided explanations, corrected AI-generated responses when necessary, and offered feedback. Thus, AI did not replace the instructor but complemented pedagogical interaction. Several statistical methods were employed to test the hypotheses. An independent samples student's t-test was used to compare post-test mean scores between the experimental and CGs. ANOVA was applied to examine the effects of each independent variable and its interactions. In addition, a linear regression analysis was conducted, with post-test scores as the dependent variable and group size, lesson duration, and frequency of AI use as explanatory variables. The threshold for statistical significance was set at $p<0.05$. To assess practical significance, effect sizes were also calculated: Cohen's d for the t-test and η^2 (eta squared) for ANOVA to estimate the proportion of variance in outcomes explained by the respective factors.

2.2. Sample

The study involved 95 students represented the following three universities: RUDN University (Russian Federation), I.M. Sechenov First Moscow State Medical University (Sechenov University) (Russian Federation), and L.N. Gumilyov Eurasian National University (Kazakhstan). Kazakh and Russian students were in China at the time of the study under a special educational exchange program. The sample size (n=95) was determined based on the total number of students who participated in the educational exchange program during the reporting period and ensures representativeness at a 95% confidence level and an acceptable sampling error of less than 5%. The age of the students was 18 to 25 years, with an average of 21 years. The gender aspect was considered in the sample: 56% of participants were men and 44% were women.

The participants were randomly selected from the general pool of students from different faculties (philology and philosophy) and years of study. The selection was made using a simple random sample with a random number generator: each student in the total population was assigned a number, and random values were generated programmatically to determine inclusion in the study. Inclusion criteria were determined by the active use of AI systems by the participants. The students studied the subject "History of China" using ChatGPT; none of the students had studied this subject prior to the study. In addition, the study involved 6 teachers. They were highly qualified specialists in the field of history, had a master's degree, and more than 9 years of work experience. These teachers developed the training program, conducted the training, and evaluated the participants.

2.3. Study procedure

At the baseline stage of the study, the teachers conducted a preliminary assessment to confirm the equality of the groups in terms of the level of prior knowledge of the main Chinese history concepts. The participants took part in online testing on the Google Forms platform, which lasted 60 minutes. The tests were administered by independent teachers. The teachers also reviewed the test answers.

Following the preliminary assessment, the participants were divided into two groups with a different number of students in each group and a different class duration. The CG consisted of 75 students and took 90-minute classes, while the EG included 20 students and took 60-minute classes. Both groups used ChatGPT (Generative pre-trained transformer), a specialized intelligent AI chatbot. These chatbots were configured for personalized learning, allowing students to receive personalized support and educational materials. Each student created their personal profile in the GPT chat server. In order to use ChatGPT and access the required interaction platforms (Google Forms, Google Meet), the students had to use computers with an internet connection.

In the CG, ChatGPT was used by a large audience of students, while in the EG, the emphasis was placed on a more intensive and personal teacher-student interaction. The study lasted 12 weeks. The difference between the student groups is shown in Table 1.

Table 1. Difference between CG and EG

Group	Number of participants	Class duration	Total duration of the training	Learning method	Application of technology
CG	75	90 min	12 weeks -1 class per week.	The use of AI technologies by a large number of students	Automated analysis of texts, archives and archaeological finds. Prediction of the possible consequences of the decisions made by political and economic leaders. Creation of personalized programs for studying history based on the individual student needs. Automated detection and analysis of socio-cultural shifts with the help of AI.
EG	20	60 min		The use of AI technologies focused on teacher-student interaction	

Students of both groups studied the following topics:

- Dynamics of socio-political events: AI was used to analyze large volumes of historical documents and archaeological finds to obtain a deep understanding of the dynamics of events.
- Development of culture and art: the students applied AI to recognize art styles, and used a personalized approach to determine the impact of art on society.
- Economic transformations: the students used machine learning algorithms to study economic changes and their impact on historical development.
- Great historical events and conflicts: in this case, AI was used to analyze major wars, social conflicts, and determine the factors that contributed to or hindered their occurrence.
- The role of emperors and political leaders: text analysis algorithms were used when studying this topic to analyze the speeches and actions of political leaders, as well as their impact on China and its society.
- Social change and reforms: AI was used to analyze reform movements, their impact on social groups, and the effectiveness of reforms.
- Interactions with other cultures: when studying this topic, the students learned about China's contacts with other cultures; AI was used to identify mutual influence and cultural exchanges.
- The role of technologies in the development of the country: AI was used to explore the impact of technology on China's scientific and economic development.

These topics enable the use of AI to gain a deeper understanding of historical processes and create personalized approaches to the study of Chinese history. The students used AI in the following way: they asked ChatGPT to provide information about certain historical events, eras, or specific historical figures based on the topic of the lesson (for example: "when was the Shang Dynasty founded in China?"). Next, students received answers from ChatGPT regarding complex concepts or historical events (e.g., "can you explain what the causes and effects of the Taiping Rebellion in China were?"). In the chat, the students discussed different aspects of historical events, analyzed different points of view, and debated their meaning (for example: "why do you think the modern Republic of China was founded?"). Moreover, the students could ask ChatGPT to provide additional materials for in-depth study of the topic ("can you recommend books or articles about the History of modern China?").

Upon completion of the training, both groups were given a final test covering the topics studied. The test results were evaluated by teachers and used to determine the impact of student number and class duration on the effectiveness of using AI in university education. The testing took place online on the Google Forms platform and lasted 90 minutes.

2.4. Research tools

To evaluate the effectiveness of AI-assisted learning, a test method was used to assess students' academic performance and mastery of Chinese history. The tests were evaluated by history teachers-each of the two tests consisted of 9 questions with no pre-submitted answer options. The maximum number of points for a single test was 100.

The pretest and posttest questions are presented in Tables 2 and 3. These tests were widely used in Chinese educational institutions. In addition, they were adapted specifically to this study, which allowed the teachers to objectively measure the academic and personal achievements of students. The reliability of the tests was ensured using statistical methods, such as the calculation of Cronbach's alpha coefficient. The obtained values of the reliability coefficient exceeded the threshold level: 0.77-pre-testing, 0.75-post-testing. The methodology's validity was also ensured by calculating the concordance correlation coefficient, which yielded a value of 0.69, confirming its high validity.

Table 2. Pretest questions

No.	Questions
1.	The Shang Dynasty: When was the Shang Dynasty founded in China?
2.	The Great Wall of China: Which dynasty started the construction of the Great Wall of China?
3.	Confucianism: Who is the founder of Confucianism?
4.	The Taiping Rebellion: When did the Taiping Rebellion take place in China?
5.	Cultural Revolution: Who was the leader of the Cultural Revolution in China?
6.	Modern Republic of China: When was the modern Republic of China founded?
7.	Taoism: What text is fundamental to Taoism?
8.	Ming Dynasty: When did the Ming Dynasty end and the Qing Dynasty begin?
9.	Opium Wars: Which country did China fight during the Opium Wars?
10.	China's Golden Age: When did China's "Golden Age" begin in the Middle Ages?

Table 3. Posttest questions

No.	Questions
1.	What cultural era in Chinese history served as the basis for the development of Confucianism?
2.	Which dynasty ruled in China during the construction of the Great Wall of China?
3.	What historical event is associated with the emergence of Chinese writing?
4.	What Chinese art is defined by the use of movements and postures to maintain physical and spiritual health?
5.	What period of Chinese history was a time of dynamic trade routes such as the Silk Road?
6.	Who was the great philosopher whose concept of indivisible destiny and the ethics of the true ruler had a major impact on China's political landscape?
7.	What major religious movement in China arose as a result of the dynamic mixing of Buddhism, Taoism, and Confucianism?
8.	What historical events determine the era of the Chinese empire, which included the Ming era?
9.	What is the name of the last imperial Chinese dynasty?

2.5. Data analysis

The data analysis was conducted using SPSS statistical analysis software (version 25.0). Statistical tests such as student's t-test, analysis of covariance (ANCOVA), and correlation analysis were used to determine the effectiveness of the training program and compare the two groups. Student's t-test was used to compare the mean values of learning efficiency between the experimental and CGs. This test is effective in determining statistically significant differences between two independent groups. ANCOVA was chosen to measure the baseline level of the students' educational competence, which reduced initial differences when comparing the groups. Correlation analysis was conducted to identify relationships among parameters such as student number and class duration.

2.6. Ethical issues

The participants signed an informed consent to participate in the current study. The collected data were processed using strict confidentiality principles, which ensured complete anonymity of the participants. Data security and privacy were a high priority, and no information was used to identify individuals. In addition, the study was conducted in accordance with the established national and international ethical standards for scientific research, adhering to all applicable norms and requirements.

2.7. Limitations

The first limitation is that the study is based on a small sample (95 students), which may limit the generalizability of the results to a wider population. The second limitation concerns the fact that only Russian and Kazakh university students participated in the study. Finally, the study did not take into account the gender of participants.

3. RESULTS

Figures 1-4 show the students' interaction with the AI chat. The students asked questions, received explanations from AI on any topic or issue, discussed historical aspects, and asked the chat to recommend additional materials. Table 4 presents the mean learning efficiency scores for the EG and CG. As we can see, the EG has a higher mean score on both the pre-test (72.9) and the post-test (85.6) compared to the CG, with mean scores of 73.0 and 76.3, respectively. According to the student's t-test, there is a statistically significant improvement in learning efficiency in the EG ($p<0.05$). Such results suggest that the impact of student number and class duration on the effectiveness of AI-assisted learning under the specified conditions of the experiment was positive.

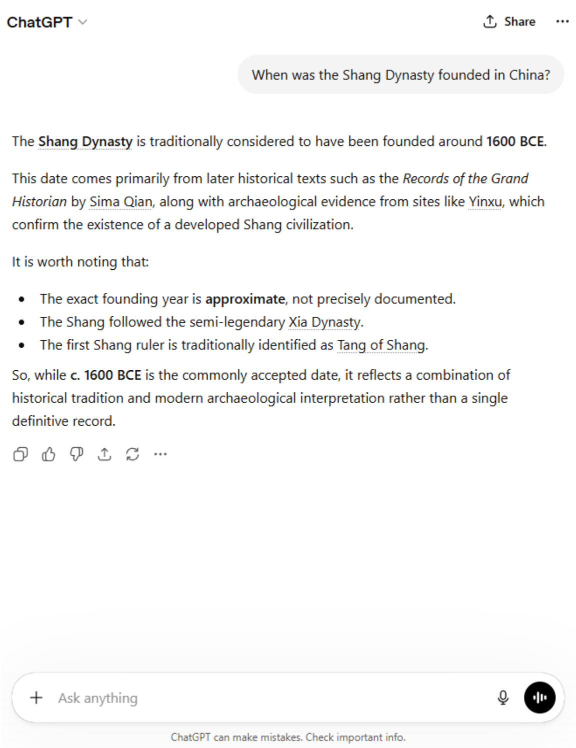

Figure 1. Asking the question: when was the Shang Dynasty founded in China?

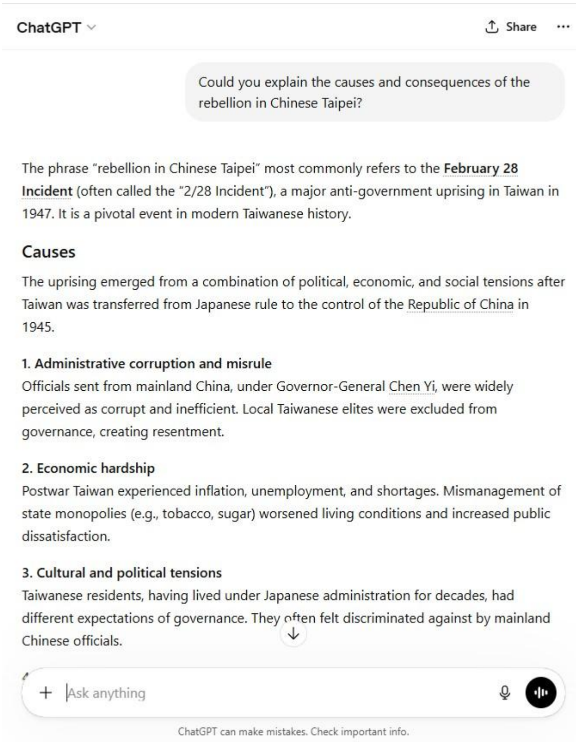

Figure 2. AI explanations of complex concepts or historical events: can you explain what were the causes and effects of the Taiping Rebellion in China?

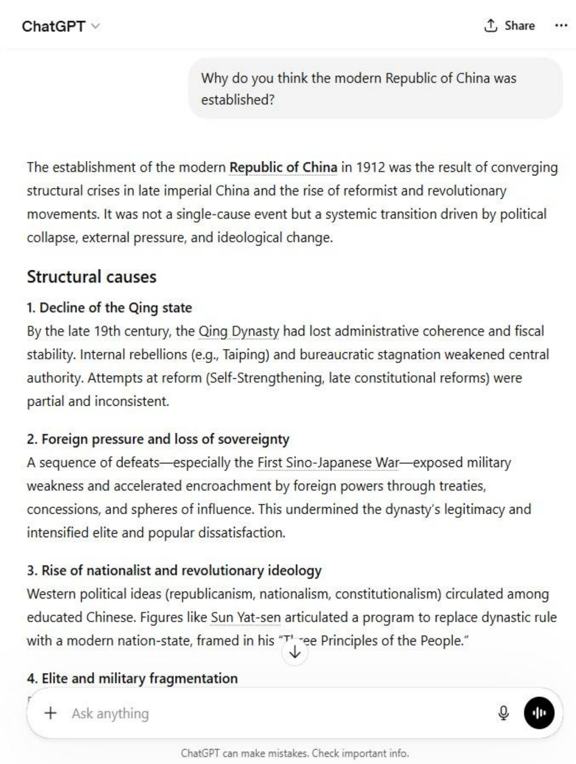

Figure 3. Discussion of historical aspects: why do you think the modern Republic of China was founded?

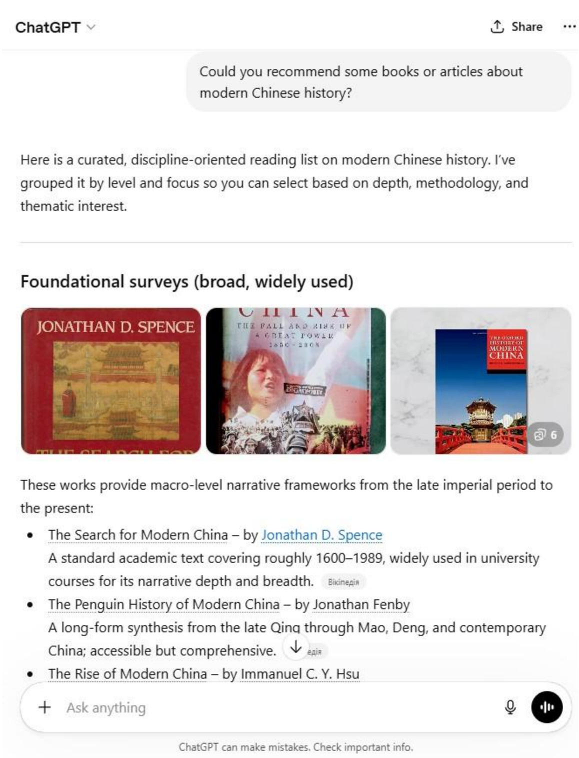

Figure 4. Additional materials: can you recommend books or articles on the history of modern China?

Table 4. Mean learning efficiency scores

Group	Number of students	Mean score (pretest)	SD	95% CI	Mean score (posttest)	SD	95% CI
EG	20	72.9	5.0	70.6–75.2	85.6	4.0	83.7–87.5
CG	75	73.0	5.5	71.7–74.3	76.3	6.0	74.9–77.7

Table 5 shows the ANOVA results, which was conducted to compare the mean scores between the EG and CG. This analysis revealed statistically significant differences in the mean scores between the groups ($p<0.001$), confirming the superiority of the EG. The obtained results demonstrate a significant improvement in learning efficiency in the EG, which was revealed by both student's t-test and ANOVA.

Table 6 contains the results of a statistical analysis of the impact of student number and class duration on the effectiveness of AI-assisted learning. The calculated p-values demonstrate the statistical significance of the results. The EG, which consisted of 20 students and took 60-minute classes, achieved a mean score of 85.7. The CG, which involved 75 students and took 90-minute classes, had a mean score of 76.3. The p-value less than 0.05 indicates statistical significance. The presented differences in mean scores between the groups are statistically significant. Thus, such parameters as student number and class duration have had an impact on the effectiveness of AI-assisted learning.

As shown in the Table 6, the EG achieved higher mean scores. These results confirm that learning in small groups and in a more teacher-student focused environment is more effective. The results of the statistical analysis show that student number and class duration have a statistically significant impact on the effectiveness of AI-assisted learning.

A smaller number of participants in the EG allowed for a more effective learning of the material and the use of individualized approaches. In contrast, the CG performed less effectively, which may suggest that an increase in the number of students can affect the quality of learning. These results confirm the hypothesis of the study. Moreover, they emphasize the importance of carefully considering the number of students and the duration of classes when introducing AI into the educational process. The optimal balance of these factors can improve the effectiveness of learning and ensure the successful integration of AI technologies into educational practice. Based on these findings, the teachers have developed several recommendations for the optimal implementation of AI for both large and small group learning in Table 7. These recommendations will help optimize the implementation of AI technologies in both large and small groups, ensuring effective and personalized learning.

Table 5. The results of the ANOVA

Source of variance	SS	DF	MS	F	p-value	η^2
Groups	1234.56	1	1234.56	18.72	<0.001	0.73
Residual	456.78	110	4.16			
Total	1691.34	111				

Table 6. The impact of student number and class duration on learning effectiveness

Group	Number of students	Class duration	Mean score	SD	95% CI	p-value	Cohen's d
EG	20	60 min	85.6	4.0	83.7–87.5	0.015	1.65
CG	75	90 min	76.3	6.0	74.9–77.7	0.042	–

Table 7. Recommendations for implementing AI into educational practice

Recommendation	Large student groups	Small student groups
Adaptation to group size	Use interactive platforms and tools that enable AI-based personalized learning for each student. Provide access to online resources and exercises that can be accessed by a large number of participants simultaneously.	Use integrated learning management systems and analytics to track individual progress. Enable effective interaction between group members through the use of specialized AI platforms and tools.
Personalization of learning	Use recommendation systems and adaptive courses to adapt materials to individual student needs. Provide students with the ability to receive additional assistance and individual advice through AI.	Develop AI-powered personalized learning plans for each student based on their needs and interests. Use data analysis to continuously improve these plans.
Effective use of analytics	Use analytics to track overall group progress and identify potential challenges. Provide students with the means to self-monitor and evaluate their progress.	Analyze data of individual students and conduct personalized interventions based on analysis results. Use analytics to evaluate effectiveness and improve teaching approaches.
Interaction and cooperation	Create virtual forums and groups for discussing materials and joint problem solving. Use AI to facilitate collaboration and exchange of ideas.	Provide interaction opportunities for students. Use AI tools for joint problem solving and collaboration.
Real-time learning	Implement instant feedback and assessment systems to immediately respond to student needs.	Use AI technologies to provide immediate, personalized feedback and adjust content in real time.

4. DISCUSSION

In this day and age, people have a variety of learning performance preferences in different learning environments [38], [43]. Different course settings and teaching methods, such as increased class size ("mega section"), online/hybrid courses, and classroom technology, are expected to play a critical role in student learning and, ultimately, students' academic success [38]. The increase in class sizes and the introduction of educational technology are two notable changes in higher education over the past few years [20], [38].

The development of AI has brought computer-assisted education into a new era. One of the recent studies concluded that by using human intelligence, a computer system can serve as an intellectual mentor, a tool, or a guardian, as well as facilitate decision-making in educational institutions. Moreover, the merging of AI and education opens new opportunities for significantly improving the quality of teaching and learning. The authors also note that teachers can take advantage of intelligent systems that assist in assessment, data collection, improvement of the learning progress, and the development of new teaching strategies [44]. Students can greatly benefit from intelligent tutoring and asynchronous learning and ultimately improve their learning outcomes. The integration of AI and education is not only a transformation of education-it is also a transformation of human knowledge, cognition, and culture. AIEd is becoming a major area of research in the field of computers and education [44]. The teachers who participated in the current study developed several recommendations for the optimal implementation of AI technologies in large- and small-group learning. It is important to note that combining the recommendations of different scientists can effectively improve student learning. Researchers also highlight that learning analytics is a well-known field that focuses on the collection, measurement, analysis, and reporting of educational data [45]. In the last decade, learning analytics has received much attention as a field that lies between data science/AI, learning sciences, and design [46]. At the same time, data sources from different learning systems and educational contexts are becoming increasingly extensive, complex, and multimodal in the current era of big data [1].

The findings of the study indicate that smaller group sizes and reduced instructional load are associated with improved academic performance in advanced AI courses. This effect can be explained by the increased capacity for individualized instruction, enhanced student engagement, and more efficient content processing resulting from reduced group-related constraints and more effective allocation of learning resources. The AI-focused curriculum, combined with the competencies developed through interaction with AI tools, creates an environment in which students receive personalized recommendations tailored to their individual needs, thereby facilitating subject mastery.

These findings are largely consistent with prior research. For example, a follow-up study on operations management courses [38] demonstrated that group size alone did not produce statistically significant differences in baseline academic performance; however, the integration of key technologies, such as interactive response systems, was associated with higher average performance, although not all effects reached statistical significance [38], [47]. This suggests that the effectiveness of technological integration is contingent upon specific instructional conditions and that the support of small-group learning through AI contributes to a more favorable environment for knowledge acquisition.

Similar patterns have been observed in studies of online learning [42], where increases in group size were found to negatively affect student engagement and course satisfaction. The present study further demonstrated that the EG, which participated in shorter but more structured instructional sessions, achieved the highest mean score (85.6), underscoring the importance of organizational parameters in shaping interactions with digital tools. The results indicate that the effectiveness of AI technologies depends not only on their usability but also on the optimal organization of the learning environment, including group size and patterns of use. It is also important to note that factors related to online assessment were aggregated, enabling a separate evaluation of their influence. Future research could benefit from implementing a factorial design to more precisely disentangle independent and correlated effects.

5. CONCLUSION

The results indicate that students in the EG achieved a higher mean score (85.6) on the final examination compared to those in the CG (76.3). This finding was corroborated by both the independent samples t-test and ANOVA. The magnitude of the observed effect underscores the practical significance of the differences identified under the given experimental conditions. However, several limitations should be considered when interpreting these findings. First, the variables associated with both groups were aggregated, which complicates the isolation of the contribution of each individual factor. The potential influence of covariates, such as students' academic level, the type of instructional resources, and the intensity of AI use, was not fully controlled. Another limitation concerns the unequal distribution of participants across the groups.

The practical significance of the obtained results lies in the possibility of improving the organization of the educational process in universities. Understanding the impact of the analyzed parameters on the effectiveness of AI-assisted learning can help to develop effective strategies for the implementation of AI technologies in various educational contexts. The results of the current study create a basis for developing recommendations and improving the quality of education based on the use of innovative approaches. The findings of this study can be of value to educational institution administrators, teachers, and developers of pedagogical technologies. Optimizing the number of participants and the class duration can improve the quality of education and facilitate the introduction of AI into pedagogical practice. The practical contribution of this study lies in substantiating the feasibility of small-group instruction with optimized instructional time supported by AI, a factor that should be taken into account in the planning of educational processes. The theoretical significance lies in clarifying the role of organizational learning parameters in determining the effectiveness of AI-supported learning environments.

This study questions the optimal parameters for all learning situations. In the future, it would be advisable to conduct a factorial experiment with independent variation of group size and lesson duration; test the results across different disciplines and at different student levels; include indicators of long-term academic performance and cognitive load; examine the influence of individual student characteristics (digital competence, motivation, learning style) on the effectiveness of AI use; and compare different models of AI integration (supportive, adaptive, and autonomous) into the educational process. Future research should prioritize implementing a full-factorial experimental design with independent variables, enabling the identification of both main and interaction effects. It would also be beneficial to expand the sample to include a wider range of academic disciplines and educational contexts.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
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CONFLICT OF INTEREST STATEMENT

This research has no conflict of interests.

INFORMED CONSENT

All the participants gave their written informed consent.

ETHICAL APPROVAL

The study design was reviewed and approved by the Ethics Committee of Al-Farabi Kazakh National University. The study involved students from L.N. Gumilyov Eurasian National University (Protocol No 341 of 17.09.2025).

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [AA] on request.

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