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Enhancing Higher Education through AI-Driven Personalized Adaptive Learning: Evidence from a ChatGPT-Based Strategy

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Artificial intelligence (AI) is reshaping higher education through personalized adaptive learning systems that tailor instruction to students' needs. Most evidence focuses on short-term outcomes in STEM; social sciences remain understudied. This study evaluates a ChatGPT-based personalized adaptive learning strategy in an undergraduate Political Science course at a Chinese university. The 16-week intervention integrated AI-driven activities into regular coursework. Outcomes were measured with structured assessments and student surveys. Using a quasi-experimental design with propensity score matching and difference-in-differences, we examined learning efficiency, knowledge mastery, and student satisfaction. The experimental group significantly outperformed the control group across all dimensions. Observed gains were associated with adaptive learning paths, timely feedback, and interactive engagement. These findings suggest that ChatGPT may offer benefits for social science education and may inform the design of AI-powered personalized learning in higher education. The study extends the evidence base on AI beyond STEM and highlights the importance of rigorous evaluation in real course settings.

Keywords: ChatGPT, personalized adaptive learning, higher education, political science, quasi-experiment

INTRODUCTION

In recent years, the integration of personalized learning models in education has gained significant momentum, driven by technology's potential to improve teaching and learning (Pane et al., 2014; Garrido, 2012). Among the most promising innovations is artificial intelligence (AI), which can personalize learning experiences and provide

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adaptive, individualized support for students（Koedinger et al., 2012）. AI-powered intelligent tutoring systems (ITS) have shown great promise in addressing heterogeneous student needs, promoting efficient learning, and enhancing knowledge internalization (VanLehn, 2011).

Personalized learning systems that leverage AI to tailor content to individual learners have been shown to increase learning efficiency and foster deep knowledge retention, particularly in technical subjects (Sweller, 1988). However, most research has focused on science, technology, engineering, and mathematics (STEM), while applications in the humanities and social sciences, particularly political science, remain underexplored. Fields such as political science present distinct challenges, including the need to foster critical thinking, navigate ideological sensitivities, and develop policy analysis skills, which traditional learning models fail to address effectively. Static feedback and one-size-fits-all learning paths can hinder engagement with complex material and limit students' academic potential.

Most studies assess the short-term effects of personalized learning systems, while the long-term impacts on learning behaviors and academic achievement remain underexplored (Phobun & Vicheanpanya, 2010). These gaps highlight the need for comprehensive research on the potential of AI-driven personalized learning to foster critical thinking and analytical skills, which are central to social science education (Ally, 2019).

In this study, we evaluated the effectiveness of a ChatGPT-based personalized adaptive learning (PAL) system in an undergraduate political science course in China. We used a single-site design at one university, integrating AI-driven instruction throughout a full semester and collecting data through structured assessments and student surveys to evaluate learning outcomes. By delivering customized learning paths and real-time, tailored feedback, the PAL system aimed to improve student engagement and learning performance while addressing the specific demands of political science education. This study contributes to the literature on AI in higher education by providing evidence on how generative AI tools can inform and reshape pedagogical approaches in the humanities and social sciences.

The findings of this study advance theoretical understanding of AI in personalized learning by identifying mechanisms that drive its effectiveness. These mechanisms include aligning content with individual student needs, reducing cognitive load, and enhancing student focus and engagement. Furthermore, this study offers practical guidance for integrating AI into social science education, particularly for cultivating students' critical thinking and policy analysis skills, which are essential to success in the social sciences.

Literature review

The integration of AI into educational practice has been transformative in higher education, particularly through its application in PAL systems (Ally, 2019). These systems use AI algorithms to analyze large datasets on student performance and behavior, enabling tailored learning paths and resources that align with each student's needs (VanLehn, 2011). By continuously monitoring progress and adapting in real time, AI-driven PAL systems provide targeted feedback and dynamic learning pathways that can enhance learning efficiency, academic engagement, and knowledge retention (Cao et al., 2020). Recent evidence also indicates that flexible course formats and AI-supported personalization can increase satisfaction and engagement by accommodating diverse learner needs (Razali & Tasir, 2025). In language-learning contexts, learners and teachers report the usefulness, personalization, and adaptability of AI tools, while acknowledging practical challenges (Benek, 2025). In disciplines such as political science, where course content is often intricate and multi-dimensional, this approach helps students navigate complex theories and fosters durable understanding.

Empirical studies also suggest that AI-driven PAL systems can improve student achievement (VanLehn, 2006). For example, a study evaluated an AI-based PAL platform and found that students who used the system outperformed peers in traditional, non-adaptive settings, attributing gains to timely, context-specific feedback and adjustment of tasks to individual progress. Complementary quasi-experimental evidence shows significant gains in English academic writing when students used ChatGPT as a structured support tool, indicating benefits beyond self-reports (Hongxia & Razali, 2025). Similarly, an AI-supported ChatGPT intervention improved students’ emotional and psychological well-being, suggesting that generative AI can bolster affective conditions that support learning (Alshammari, 2025). The personalized support provided by PAL systems appears especially beneficial for students struggling with specific concepts, offering supplemental materials targeted to identified gaps and promoting a more inclusive learning environment.

Despite these promising outcomes, the literature highlights several challenges associated with deploying AI-driven PAL systems in educational settings. A primary concern is algorithmic bias, which can perpetuate inequities in learning opportunities. AI models are often trained on data that reflect existing biases, reinforcing educational disparities (Tapalova & Zhiyenbayeva, 2022). For example, a system trained largely on data from specific demographic groups may fail to support students from underrepresented backgrounds, exacerbating the digital divide. Furthermore, effective implementation requires substantial technical infrastructure, expertise, and resources that may not be readily accessible to all institutions, particularly those in resource-constrained settings. Even when institutions adopt AI or AI-adjacent innovations, instructors report workload pressures, assessment integrity concerns, and support needs that must be addressed for successful scaling (Razali & Tasir, 2025; Benek, 2025). These constraints present a significant barrier to scalability, especially in less affluent or rural contexts.

Although the benefits of AI in personalized learning are widely recognized, whether these systems consistently improve educational outcomes remains contested. Pane (2014) suggested that effectiveness depends on contextual factors such as students’ prior knowledge, engagement levels, and the adaptability of the learning environment. In disciplines such as political science, where critical thinking, policy analysis, and argumentation are emphasized, the value of AI depends on its capacity to support higher-order cognitive skills. Fu (2022) argued that well-designed, AI-driven platforms can enhance students’ critical thinking by presenting complex political scenarios and theories in ways aligned with learners' cognitive readiness. However, success depends on the ability to respond dynamically to students' evolving understanding and to engage them in deep, reflective learning. Emerging design work also indicates that prompt engineering with ChatGPT can be used to construct inquiry tasks and modeling activities targeting higher-order thinking, though pedagogy and guidance remain pivotal (Dertli & Yıldız, 2025).

Despite these challenges, the literature points to the substantial promise of AI-driven PAL systems in higher education (Song & Wang, 2020). In political science, AI can personalize support to help students engage with sophisticated subject matter (Almuhanna, 2024). Real-time feedback, adaptive materials based on performance, and tailored supplemental resources are increasingly recognized as key to improving academic achievement and student engagement (Ikedinachi et al., 2019). As these technologies evolve, ethical considerations, including addressing algorithmic bias and ensuring equitable access, must remain central.

Future research should examine the long-term effects of AI-driven PAL systems on learning outcomes (Wilson & Scott, 2017). Studies are also needed to assess their capacity to foster critical thinking, problem-solving, and analytical skills, which are central to political science. Moreover, work on scalability should consider diverse educational settings and develop strategies to mitigate bias, infrastructure constraints, and resource limitations. Expanding this line of inquiry is essential to understanding AI's role in enhancing the educational experience in complex, multifaceted fields such as political science.

Theoretical framework and research hypotheses

This study is grounded in the principles of PAL and leverages generative AI (e.g., ChatGPT) to enhance educational outcomes. By integrating theories of personalized learning, cognitive load, and student engagement, we developed a framework for using AI-driven tools to optimize learning through real-time, personalized support. Figure 1 presents the study's theoretical framework.

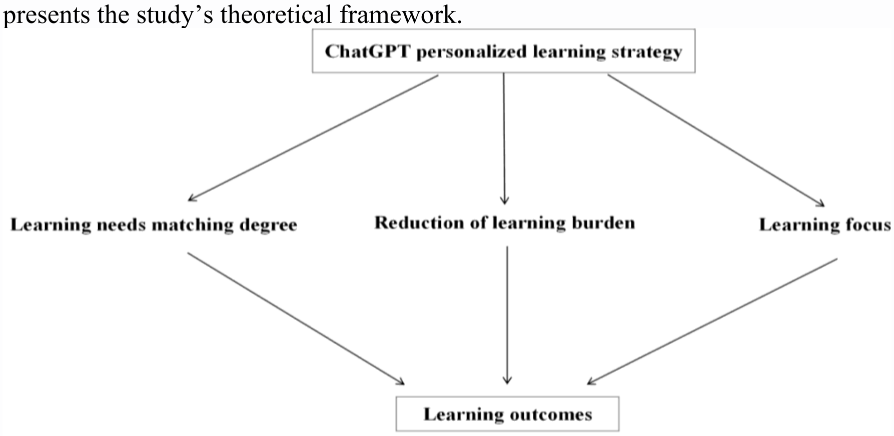

Figure 1
Theoretical framework of the ChatGPT-based personalized adaptive learning strategy

Personalized adaptive learning and generative artificial intelligence

Generative AI offers a novel approach to PAL by leveraging advanced natural language processing and real-time content generation. Systems such as ChatGPT provide dynamically tailored content, including customized learning recommendations, instant feedback, and interactive explanations, based on learners' profiles (Wilson & Scott, 2017). Real-time adaptability allows these systems to adjust to learners' evolving needs, a core principle of personalized learning (VanLehn, 2006). This capability can reduce the time required to complete learning tasks and enhance content mastery and overall learning experience (Cao et al., 2020). Therefore, we propose the following hypothesis:

H1: Students who engage in PAL strategies using ChatGPT will demonstrate significantly better learning outcomes than those using traditional teaching methods.

This hypothesis is based on the argument that personalized learning, particularly when facilitated by AI tools, is more effective than traditional one-size-fits-all approaches. By dynamically adjusting learning content based on student progress and needs, generative AI tools can foster more efficient learning and lead to better knowledge retention and application than traditional approaches.

Personalized learning theory and learning needs matching

The personalized learning theory posits that when learning content is tailored to students' cognitive levels and interests, they are more likely to engage deeply and achieve positive academic outcomes (Pane et al., 2014). A key mechanism by which personalized systems improve outcomes is the precise matching of learning content to students' individual needs (Phobun & Vicheanpanya, 2010). This process increases the relevance of tasks and enhances students' motivation and engagement (Phobun & Vicheanpanya, 2010). By aligning learning tasks with students' abilities and interests, ChatGPT creates an environment in which students perceive content as valuable and invest cognitive resources in the learning process (Huang & Liaw, 2020; Qu et al., 2022). Therefore, we proposed the following hypothesis:

H2: The precision of needs matching positively mediates the relationship between personalized learning strategies and learning outcomes.

This hypothesis is based on task value theory, which suggests that when students perceive tasks as valuable, engagement increases (McLaren et al., 2017). In AI-driven adaptive learning, the system's ability to match tasks to student needs raises task value, which, in turn, amplifies engagement and enhances academic performance.

Cognitive load theory and reducing learning burden

Cognitive load theory posits that learners have limited cognitive resources for processing new information (Sweller, 1988). When learning tasks are overly complex or impose extraneous cognitive load, students may struggle to retain and apply content effectively (Holstein et al., 2018). Generative AI tools such as ChatGPT can alleviate cognitive load by streamlining tasks, offering simplified explanations, and providing real-time feedback that helps students organize information more efficiently (Tapalova & Zhiyenbayeva, 2022). Through these mechanisms, AI can reduce unnecessary cognitive load and enable students to focus on essential tasks, thereby improving learning efficiency. Therefore, we propose the following hypothesis:

H3: Reduced cognitive load (learning burden) positively mediates the relationship between personalized learning strategies and learning outcomes.

This hypothesis is grounded in cognitive load and information-processing theories, which hold that reducing unnecessary cognitive distractions enhances students' ability to encode, store, and retrieve information effectively (Celik, 2023). By simplifying task complexity and offering immediate feedback, AI systems reduce cognitive burden and allow students to focus on mastering core concepts, thereby enhancing overall learning outcomes (Chen et al., 2020).

Cognitive engagement theory and focused learning

Learning engagement, particularly sustained focus, is critical for academic success. Cognitive engagement theory posits that deep task engagement drives learning outcomes, with sustained attention facilitating higher-order cognitive processes such as analysis and problem-solving (Aji & Khan, 2019). Tools such as ChatGPT help students maintain focus by minimizing distractions and providing clear, task-oriented goals. By offering instant feedback and personalized content, AI systems enable students to remain engaged, reduce external distractions, and optimize attention allocation (Akomolafe & Adesua, 2016). Therefore, we propose the following hypothesis:

H4: Learning focus positively mediates the relationship between personalized learning strategies and learning outcomes.

Attentional resource allocation theory holds that students who direct cognitive resources to the most important aspects of learning, without being distracted by irrelevant information, achieve higher levels of understanding and retention (Altbach & de Wit, 2019). ChatGPT facilitates effective learning by enhancing students' focus, thereby contributing to improved performance in knowledge mastery and cognitive tasks (Song & Wang, 2020).

METHOD

Sampling design

We used a quasi-experimental design with rigorous matching to ensure comparability between the experimental and control groups. Participants were drawn from an undergraduate Political Science program at [institution name, country, if applicable], a [public/private] university, across two consecutive academic years. The 2022 cohort (n = 149) served as the control group, and the 2023 cohort (n = 155) comprised the experimental group, yielding a total sample of 304 students. Sample size was determined by power analysis and feasibility, ensuring adequate power to detect meaningful between-group differences. Using consecutive cohorts minimized cross-group contamination because students in different years did not interact academically. It also aligned with the instructional cycle, enhancing external validity and practical relevance.

To strengthen internal validity, we controlled key variables, including academic background, admission scores, course content, and instructional team, to minimize baseline differences. Inclusion criteria required full-time undergraduates in the political science program with no prior exposure to AI-assisted learning environments. Students with prior ChatGPT-supported learning or those who declined informed consent were excluded. Participants were recruited through university email invitations, course announcements, and in-class presentations to maximize awareness and voluntary participation.

Ethical considerations were integrated throughout the research process. The study followed ethical guidelines for experimental research in China. The university reviewed and approved the experimental design. The university's academic committee and the student union provided oversight to ensure compliance with guidelines for research involving human participants. Prior to enrollment, all students provided written informed consent after being fully briefed on the study's objectives, procedures, potential benefits, and risks. Participants were assured of confidentiality; data were anonymized and securely stored to prevent unauthorized access. Students could withdraw from the study at any time without academic or personal consequences.

Of the 356 initially recruited participants, 52 were excluded from the final analysis due to incomplete participation, data inconsistencies, or withdrawal. The final analytic sample comprised 304 students who completed the intervention. Adherence to ethical standards and a rigorous sampling design support the study's scientific credibility and methodological robustness, providing insights into the role of AI-driven adaptive learning in higher education.

Experimental process

The intervention spanned one academic semester and comprised three phases: preparation, implementation, and assessment.

Preparation phase

Before the study, we standardized the intervention through several preparatory steps. We modularized the course into thematic units to enable ChatGPT to deliver tailored content and generate personalized recommendations aligned with each student's progress. We also developed a dynamic feedback system and trained instructors and teaching assistants to systematically record student interactions on the ChatGPT platform. These steps ensured consistent data collection and supported subsequent analyses of learning trajectories and engagement patterns.

Implementation phase

During the semester, both groups received identical course content, but their instructional modalities differed. The experimental group participated in a blended format integrating classroom instruction with ChatGPT-supported PAL. Students could choose among multi-tiered resources (basic, intermediate, advanced) that were dynamically adjusted to their performance and learning needs. For example, in the policy diffusion module, students with a strong foundation received advanced theoretical materials and recent research, while those needing support received simplified explanations and guided exercises. Teaching assistants regularly uploaded students' stage test responses to the ChatGPT system, which identified knowledge gaps and generated targeted remedial tasks in real time.

The control group received conventional instruction. Instructors delivered standardized lectures and assignments, and all students progressed at a uniform pace set by the syllabus. Without the adaptive features of ChatGPT, the control group's learning experience remained limited to traditional methods.

Assessment and data collection

To evaluate the efficacy of the personalized adaptive intervention, both groups completed 10 standardized assessments administered at regular intervals throughout the semester. These assessments were identical for both groups, providing consistent measures of knowledge acquisition and conceptual understanding. Furthermore, students in the experimental group completed a structured questionnaire designed to capture qualitative data about their experiences with the AI-driven learning process, including their perceptions of engagement, comprehension, and overall satisfaction.

All quantitative and qualitative data, including test scores, survey responses, and relevant demographic information, were aggregated into a comprehensive dataset. This dataset underwent systematic cleaning and coding to ensure data integrity, enabling robust statistical analyses to assess the impact of PAL strategies on student outcomes.

Quantitative analysis

Based on the data collected during the experiment, we tested the research hypotheses using quantitative methods.

Variables and data sources

The dependent variable was students' learning effectiveness, measured in three dimensions: learning efficiency, knowledge mastery, and learning satisfaction. Learning efficiency was operationalized as the time required to complete course tasks, reflecting the speed at which students achieve their learning goals. Knowledge mastery was assessed by monthly stage assessments, each scored out of 100, which gauged students' understanding of the core concepts of the course. Learning satisfaction was measured using students' evaluations of the teaching mode on a five-point Likert scale (1 = very dissatisfied; 5 = very satisfied). These measures were collected monthly over four observation periods for both groups.

The independent variable was learning mode, which differentiated the ChatGPT-supported PAL strategy from traditional teaching methods. In this study, students in the experimental group who used ChatGPT for personalized learning were assigned a value of 1, whereas those in the control group were assigned a value of 0.

To further explore mechanisms underlying the impact of ChatGPT-supported learning strategies, this study examined three mediators: learning needs match, reduced learning burden, and learning focus. Learning needs match captured the extent to which students perceived that the personalized strategies provided by ChatGPT aligned with their individual learning needs; this was measured by asking respondents to rate the statement "The learning strategies recommended by ChatGPT match my learning needs very well" on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Reduced learning burden was assessed by evaluating whether students experienced decreases in burdens associated with information retrieval, content understanding, information redundancy, learning plan formulation, and theoretical organization. Each aspect was recorded as a binary variable (1 if a reduction was perceived, 0 otherwise) and aggregated into a total score. Learning focus was measured on a five-point Likert scale by evaluating the degree of sustained attention and engagement students exhibited while interacting with ChatGPT.

To enhance the internal validity of the model, control variables related to students' family background, personal characteristics, and peer support were included. These data were collected using questionnaires designed to reduce potential confounding influences on learning effectiveness. Detailed descriptions of all variables, their measurement scales, and data sources are provided in Table 1.

Table 1
Variable information

Variable Type	Variable	Variable Description	Data Source
Dependent	Learning Efficiency	Average time (minutes) to complete course tasks	Novel Database
	Knowledge Mastery	Monthly assessment scores (scored out of 100)	Novel Database
	Learning Satisfaction	Student evaluation of teaching (five-point Likert scale)	Survey
Independent	Learning Mode	Experimental group = 1; Control group = 0	Novel Database
Mediating	Learning Needs Match	Degree to which ChatGPT recommendations meet students' needs (five-point Likert scale)	Survey
	Reduced Learning Burden	Perceived decrease in learning burden, aggregated from binary sub-items	Survey
	Learning Focus	Degree of sustained attention and engagement (five-point Likert scale)	Survey
Control	Sex	Man = 1; Woman = 0	Survey
	Classroom Participation	Number of classroom contributions	Novel Database
	Family Income	Income level (1 = low; 2 = middle; 3 = high)	Survey
	College Entrance Exam Score	Provincial college entrance exam ranking	Survey
	Peer Support	Receipt of peer learning support (Yes = 1; No = 0)	Survey

Model selection

This study employed a methodological framework combining propensity score matching (PSM) and difference-in-differences (DID) to assess the impact of ChatGPT-supported PAL on student outcomes. PSM created comparable experimental and control groups by matching key covariates, reducing selection bias and strengthening the internal validity of causal inferences. DID measured changes in learning outcomes before and after the intervention, helping isolate the impact of the instructional mode while accounting for potential systematic bias.

We also conducted a mediation analysis to identify the mechanisms through which ChatGPT-supported strategies influence learning. This analysis examined the mediating effects of learning needs match, reduced learning burden, and learning focus. By integrating PSM, DID, and mediation analysis, the study evaluated overall effectiveness and the processes through which PAL enhances educational outcomes. This comprehensive approach aims to offer nuanced insights for educational theory and practice.

Econometric results

Propensity scores were generated using a logistic regression model, and participants were matched on sex, college entrance exam scores, and family income. Subsequently, nearest-neighbor matching (1:1 with a caliper of 0.1) was applied to students in the experimental and control groups, ensuring comparability of baseline characteristics. After matching, 92% of the total sample was successfully paired, with 8% unmatched. The pseudo-R^2 decreased from 0.15 before matching to 0.02 after matching, and the likelihood ratio test indicated that baseline differences between the groups were no longer statistically significant ($p > 0.1$). Sensitivity analyses using kernel and radius matching yielded consistent results, with learning efficiency in the experimental group significantly higher than in the control group. These findings reinforced the robustness of the results.

Table 2 presents the DID results. Models 1 and 2 used learning efficiency as the dependent variable, Models 3 and 4 used knowledge mastery, and Models 5 and 6 used learning satisfaction. These models served as mutual robustness checks, and their consistent results substantiated the study's scientific rigor and reliability. Additionally, the DID models passed tests for multicollinearity (all variance inflation factors < 10) and heteroscedasticity (Breusch–Pagan test, $p > 0.05$), confirming that estimates were robust and consistent with econometric assumptions.

Table 2
DID model results

Variables	Learning Efficiency		Knowledge Mastery		Learning Satisfaction	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Core Variable						
Treatment × Post	1.762***	0.576**	3.217***	3.595***	2.695***	2.701**
	(−0.441)	(−0.29)	(−0.897)	(−0.662)	(−1.135)	(−1.341)
Treatment	1.215***	0.912**	12.85**	14.52*	2.054***	1.900**
	(−0.324)	(−0.311)	(−5.891)	(−7.679)	(−0.478)	(−0.542)
Post	0.271	0.198	−9.802	−14.13	−1.911	−2.064
	(−0.791)	(−0.812)	(−6.242)	(−14.4)	(−1.731)	(−1.816)
Mediating Variables						
Learning Needs Match		4.474**		46.29***		2.285*
		(−2.08)		(−17.79)		(−1.327)
Reduction in Learning Burden		2.477***		61.76***		5.795**
		(−0.816)		(−13.41)		(−2.861)
Learning Focus		0.981**		23.48***		0.135**
		(−0.366)		(−7.864)		(−0.065)
Control Variables						
Sex	−0.782**	−0.844**	−9.175**	−9.261**	−2.315**	−2.268**
	(−0.329)	(−0.382)	(−3.291)	(−6.418)	(−0.612)	(−0.644)
Family Income	0.322***	1.632*	1.628**	1.671**	0.162**	0.221**
	(−0.072)	(−0.937)	(−0.773)	(−0.777)	(−0.061)	(−0.098)
College Entrance Examination Score	0.108**	0.102*	0.138**	0.127***	0.235**	0.127***
	(−0.057)	(−0.062)	(−0.061)	(−0.049)	(−0.093)	(−0.049)
Peer Support	−0.026	0.193	−0.041	−0.025	−0.033	−0.025
	(−0.024)	(−0.136)	(−0.031)	(−0.211)	(−0.029)	(−0.211)
Constant	12.85***	12.98***	13.21***	14.72***	6.784***	6.974***
	(−4.821)	(−4.981)	(−4.793)	(−5.234)	(−1.214)	(−1.272)
Observation	2128	2128	2128	2128	2003	2003
R-squared	0.241	0.281	0.282	0.354	0.325	0.378

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FINDINGS AND DISCUSSION

The findings demonstrate that ChatGPT-supported PAL significantly improves learning efficiency, knowledge mastery, and learning satisfaction compared with traditional teaching methods. The experimental group consistently outperformed the control group across all three dimensions, suggesting that AI-driven personalization enhances student engagement and academic performance. Recent studies in higher education (Daha & Altelwany, 2025) report that ChatGPT can function effectively as a virtual tutor, helping learners set goals, design personalized plans, and monitor progress, and these findings align with our observed improvements. These results align with prior research on AI-assisted education while extending its applicability to the social sciences.

The improvement in learning efficiency indicates that students in the experimental group completed tasks more quickly while maintaining comprehension, suggesting that adaptive learning paths reduce cognitive load and streamline the learning process. Recent frameworks within Digital Learning Ecosystems emphasize AI-enabled, flexible, and collaborative learning environments, reinforcing the role of ecosystem design in supporting personalization and efficiency (Daha & Altelwany, 2025). This aligns with studies in STEM education, where AI-powered personalized learning has been found to accelerate problem-solving and improve time-on-task efficiency (Koedinger et al., 2012). While prior research emphasizes algorithm-driven adaptability in structured disciplines, this study confirms that similar AI-based strategies benefit conceptual and discourse-heavy subjects such as political science, where analytical thinking is key.

The improvement in knowledge mastery reinforces the effectiveness of AI-driven learning. The experimental group demonstrated higher test scores and stronger conceptual understanding, which is consistent with literature indicating that AI-assisted instruction enhances content retention and deeper learning (Pane et al., 2014; VanLehn, 2011). Unlike prior studies focused on adaptive learning in procedural domains (e.g., mathematics and coding; Alshammari, 2025), this study provides evidence that AI can also support complex, discussion-based learning by facilitating targeted reinforcement and scaffolding. This expands AI's applicability beyond technical subjects.

Similarly, learning satisfaction was significantly higher in the experimental group, suggesting that personalized, AI-driven learning environments foster greater engagement and motivation. This finding aligns with research showing that adaptive AI-based feedback increases student interest and reduces frustration. Unlike earlier studies that raised concerns about over-reliance on AI reducing the role of instructors (Thuy, 2025), this study suggests that ChatGPT complements rather than replaces traditional teaching by offering scalable, individualized support alongside classroom instruction.

Additionally, the results of the control variable analysis indicated that sex, economic conditions, and academic background were significant determinants of learning outcomes, whereas peer support and classroom participation appeared relatively diminished in the personalized learning mode. Across all models, sex showed a significant negative effect on learning outcomes, suggesting that sex differences may influence students' abilities to adapt to the instructional mode. In contrast, family economic status showed a significant positive effect, indicating that students from more affluent backgrounds tended to benefit more from personalized learning strategies. The positive impact of college entrance exam scores suggested that students with a stronger academic foundation had greater potential for improvement in learning efficiency, knowledge mastery, and learning satisfaction. Conversely, peer support and classroom participation were not statistically significant in any model, implying that these traditionally important social and engagement factors were attenuated in personalized learning environments.

Despite these contributions, the study has several limitations. First, the sample was drawn from a single institution, which limits the generalizability of the findings to other universities and academic settings. Future research should include multi-institutional and cross-cultural comparisons to assess the broader applicability of AI-driven personalized learning. Second, although key baseline variables were controlled, unobserved factors such as prior AI exposure, motivation, and self-regulated learning skills may have influenced the results. Integrating qualitative methods, such as interviews and observational studies, could provide deeper insights into students' experiences. Third, this study examines short‑term outcomes only. Longitudinal insights from pedagogical frameworks such as motivational modeling in AI-driven contexts (Hajian et al., 2025) suggest time‑ phased gains in engagement and mastery, underscoring the need to adopt time-series designs in future research. Finally, reliance on self-reported measures of learning satisfaction and engagement may introduce response bias. Using objective behavioral data, such as learning analytics and eye-tracking technology, could strengthen the conclusions of future research.

Overall, these findings confirm the effectiveness of ChatGPT-supported personalized learning in enhancing learning efficiency, knowledge mastery, and student satisfaction in a political science course. By extending AI-assisted learning beyond STEM fields and reinforcing its role as a pedagogical aid rather than a replacement for instructors, this study contributes to the growing body of research on AI in education. Addressing the identified limitations in future research will help refine AI-driven learning strategies and expand their practical application in higher education.

In addition to these pedagogical implications, integrating generative AI into higher education requires attention to ethical governance and algorithmic transparency. Ensuring fairness, minimizing bias, and providing clear explanations of AI-generated recommendations are essential to maintaining trust and equity. Our findings indicate that the effectiveness of ChatGPT-supported PAL increases when students perceive the system as transparent and impartial, highlighting the need for governance frameworks that safeguard student rights and support sustainable AI-enhanced teaching practices.

CONCLUSION

We compared the learning efficacy of a ChatGPT-enabled PAL strategy with traditional teaching methods. The results indicated that students in the experimental group showed statistically significant improvements in learning efficiency, knowledge mastery, and learning satisfaction. These findings highlight the advantages of generative AI in enhancing academic performance within a political science course and underscore its potential to transform conventional approaches to political theory instruction.

Furthermore, this study identified three key mechanisms through which ChatGPT-supported personalized learning exerts its effects: precise matching of learning needs, reduced cognitive load, and sustained learning focus. Together, these mechanisms function as a closed-loop process comprising needs diagnosis, adaptive resource allocation, and cognitive reinforcement, strengthening students' understanding of political concepts and policy-analysis skills. Theoretically, our findings support the innovative integration of intelligent technology in political science education and offer scalable, replicable solutions for diverse instructional scenarios, such as political philosophy debates and comparative political analysis, promoting the digital transformation of political science teaching within the framework of the new liberal arts.

Future research should adopt a four-dimensional development approach encompassing horizontal expansion, vertical deepening, technological iterations, and ethical governance. First, the application of ChatGPT should extend beyond traditional liberal arts courses to interdisciplinary fields such as political economy and international relations. Second, establishing a multi-year tracking database with latent variable growth models would enable assessment of the long-term cumulative effects of generative AI on the evolution of political thought. Third, integrating eye-tracking and learning analytics to build ITS based on political science knowledge graphs could facilitate dynamic adjustment of cognitive load during instruction. Finally, given the ideological sensitivities in political science, a comprehensive governance framework that incorporates algorithmic transparency, data-bias detection, and the cultivation of digital-citizenship ethics is essential to ensure alignment with ethical standards and the discipline’s core values.

The integration of generative AI into political science education remains in its early stages; nevertheless, this study provides compelling empirical evidence for AI-supported teaching reforms. It challenges educators to rethink traditional methods of cultivating political literacy by advocating precise resource allocation through human-machine collaboration, intelligent management of learning processes, and real-time academic feedback. As technological innovation and pedagogical practices continue to evolve, the fusion of AI and political science is expected to foster an inclusive and dynamic digital education ecosystem, paving the way for versatile political science professionals equipped with advanced digital literacy.

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