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Acceptance and Influencing Factors of AI-Assisted Ideological and Political Teaching among Application-oriented University Students

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Abstract: This study focuses on the acceptance of AI-assisted ideological and political teaching (IPT) by application-oriented university students and its influencing factors. Based on the Technology Acceptance Model (TAM), an integrated model incorporating situational variables such as perceived ease of use (PEOU), perceived usefulness (PU), teaching adaptability (TA), trust (TR), perceived ethical risk (PER), social influence (SI), facilitating conditions (FC), attitude (ATT) and acceptance (ACC) is constructed, and 209 valid samples are collected via questionnaire survey for empirical testing. The results demonstrate that PEOU significantly enhances PU, and both variables positively influence students' ATT toward AI-assisted IPT. PU and ATT further contribute to students' ACC of AI-assisted teaching. TR, SI, and FC also positively affect ATT, while PER has a negative effect. Among these factors, TR and FC demonstrate particularly strong impacts. Based on these findings, this study suggests that universities should improve the usability and pedagogical alignment of AI tools, strengthen students' trust in AI-generated content, address ethical concerns, and offer adequate institutional support and training. This research extends the application of TAM in value-oriented educational contexts and provides practical implications for universities seeking to integrate AI technologies into ideological and political education (IPE).

Keywords: AI-assisted teaching; Ideological and political teaching (IPT); Application-oriented university students; Technology acceptance

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1. Introduction

Artificial intelligence (AI) technology is having a huge impact on higher education around the world. Its use in teaching support, learning analysis, personalized learning, and other areas is growing and becoming more complex. AI technology has shown a number of uses in the field of ideological and political education (IPE), covering smart recommendations for learning resources, smart question-and-answer systems, help with creating content, and analysis of learning behavior based on data. These technical references have opened up new ways to teach politics and ideas. Undergraduate colleges and universities that focus on applications are in a good position to train highly skilled application-oriented professionals. Their ideological and political teaching (IPT) still has to deal with the practical problem of how to keep up with the times and come up with new ways to teach that make it more effective and interesting. In this context, college students, as direct users and experiencers of AI-assisted IPT, their acceptance of this technology is not only related to the use efficiency of the technical tools themselves, but also affects the breadth, depth, and sustainability of the integration of AI and IPE at a deeper level. Consequently, a systematic investigation into the acceptance of AI-assisted IPT among university students, along with the underlying driving and constraining factors, holds significant practical urgency and academic merit.

2. Literature review

2.1. Application of AI technology in higher education and IPT

The application of AI in higher education has become a global research and practice hotspot. Zawacki-Richter et al. pointed out in a systematic review that "its application mainly focuses on learner support services, learning analysis and evaluation, and personalized learning path planning. At the same time, it also warned of the lack of educators' perspective in the research" [1]. In this context, learning analysis is regarded as an important tool to help educators understand complex learning processes [2]. Specifically, at the teaching level, AI technologies such as intelligent tutor systems, adaptive learning platforms, and automated assessment tools are gradually changing the traditional teaching interaction mode [3]. Focusing on the specific field of IPE and IPE, the application research of AI is still in its initial stage, but it has shown diversified exploration. For example, AI is used to realize the precise push of educational resources, intelligent diagnosis of learning problems, and dynamic tracking of the process, and the interactivity and immersion of teaching are improved through virtual simulation, intelligent dialogue, and other methods. These preliminary explorations have laid the foundation for subsequent empirical research, demonstrating the potential of AI technology in improving the effectiveness of IPT.

2.2. Theory of technology acceptance

The technology acceptance model (TAM) and its offshoot theories provide a robust theoretical framework for examining users' acceptance behavior regarding new technologies. The TAM model put forth by Davis asserts that a user's intention to utilize information technology is influenced by their attitude towards its use, which is shaped by the core beliefs of perceived usefulness and perceived ease of use [4]. Because it is easy to understand and explains things well, the model is often used in different situations where people are accepting new technology. To consolidate various theoretical frameworks, Venkatesh et al. introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as primary variables influencing the intention to use technology, while also acknowledging moderating factors such as gender, age, experience, and voluntary use [5]. The TAM/UTAUT model is commonly employed in educational technology to examine the acceptance of technologies like online learning platforms, mobile learning, and digital resources by educators and learners [6–7]. These studies have validated the relevance of classical variables in educational settings and indicate that contextual variables should be integrated based on the specific technology, educational level, and subject characteristics.

2.3. Factors influencing university students' acceptance of AI-assisted teaching

With the deepening of AI education applications, the research on factors affecting students' acceptance has become more and more detailed. Perceived usefulness (PU) and perceived ease of use (PEOU), as the core constructs of TAM, are still repeatedly verified as key antecedents in AI education scenarios, corresponding to the belief that students believe that AI can improve learning effectiveness and the belief that using AI is labor-saving and convenient. However, when AI, especially generative AI, is applied to value education courses such as IPE, pure functional beliefs may not be sufficient to fully explain acceptance behavior. Students' trust (TR) has become a prominent factor, involving trust in the accuracy, objectivity, and value orientation reliability of AI-generated content [8–9]. Meanwhile, perceived ethical risk (PER), such as concerns about AI's potential to generate erroneous or biased information, weakens independent thinking ability, causes academic integrity problems, and privacy leaks, constituting important negative influencing factors. In addition, teaching adaptability (TA), that is, the degree of matching between the functions of AI tools, the way of content presentation, and the specific learning needs of IPT courses, is also considered to be the key to influencing its perceived value and acceptance willingness [10–12]. External variables such as social influence (SI) and facilitating conditions (FC) have also been proven to have a significant effect on attitude (ATT) or acceptance (ACC) toward the use of technology in many studies [13–15].

2.4. Research gap

Reviewing the existing literature, the application research of AI in education is booming, and the theoretical system of technology acceptance is relatively mature, which provides a solid theoretical support and methodological reference for this study. However, there are still some shortcomings in the existing research. First of all, most of the studies focus on general learning technology or STEM disciplines, and there is a lack of empirical research on the acceptance of AI technology in the special and important discipline field of IPE. Secondly, in the selection of influencing factors, most of the existing studies follow the classic TAM or UTAUT framework, and the factors unique to the IPT context, such as the adaptability of value transmission, the special trust problem brought by the credibility of ideological content, and the unique ethical risks that may arise, are not deeply explored and integrated. Finally, there are not many studies on the group of undergraduates in application-oriented universities. This group has both the general characteristics of students in higher education and the particularity of applied talent training. Its technology acceptance model is worth special discussion. In order to address these gaps, this study aims to focus on students from application-oriented universities, investigate the nascent and critical intersection of AI and IPT, and enhance the classic TAM by integrating context-specific variables to develop a more comprehensive and explanatory model, thereby generating empirical findings directly relevant to the practices and policy-making within this specific educational sector.

3. Theoretical model and hypothesis

3.1. Theoretical model

This study mainly takes the TAM proposed by Davis (1989) as the core theoretical basis. The TAM model believes that the individual's intention to use a new technology is directly determined by the attitude of use, and the attitude of use is affected by the two key beliefs of PU and PEOU, in which PEOU will also positively affect PU. The model has become the starting point for the construction of the basic logical path of this study due to its simplicity and the validity verified in a large number of information technology (IT) adoption studies. However, the standard TAM model originated from the adoption of IT in organizational management, and it may be slightly thin to directly migrate it to the IPT situation with the special attributes of value guidance and ideological shaping. Therefore, this study further draws on the idea of contextualized expansion in the field of educational technology and takes the particularity of IPT into consideration. Specifically, TA is imported to reflect the core appeal of technology matching with the curriculum, TR is employed to deal with the credibility challenge when AI processes ideological content, and PER is introduced to face the cognitive and moral risks that AI applications may bring. Simultaneously, referring to theories such as UTAUT, two important external variables, SI and FC, were included to more comprehensively depict the internal and external environment that affects students' ATT or ACC toward the use of AI technology. Thus, this study constructs an integrated theoretical model, taking the core chain of the classic TAM "PEOU→PU→ATT→ACC" as the core chain (**Figure 1**).

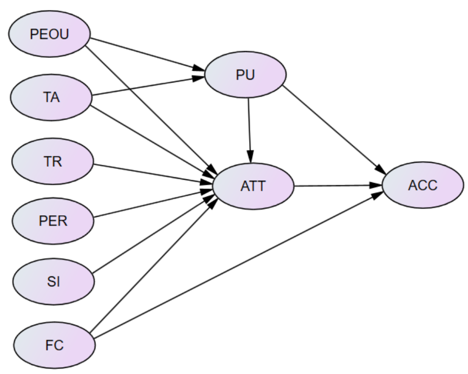

Figure 1. Theoretical model of the study

3.2. Hypothesis

Based on the core logic of TAM and the expansion of IPT context, the following research hypotheses are proposed:

H1: PEOU has a significant positive impact on PU.

H2: PEOU has a significant positive impact on ATT.

H3: PU has a significant positive impact on ATT.

H4: ATT has a significant positive impact on ACC.

H5: TA has a significant positive impact on PU.

H6: TA has a significant positive impact on ATT.

H7: TR has a significant positive impact on ATT.

H8: PER have a significant negative impact on ATT.

H9: SI has a significant positive impact on ATT.

H10: FC have a significant positive impact on ATT.

H11: PU has a significant positive direct impact on ACC.

H12: FC have a significant positive direct impact on ACC.

4. Methodology

4.1. Research design

This study adopts the questionnaire survey to conduct quantitative research. The questionnaire survey can efficiently collect the desired sample data and quantitatively test the relationship between variables, which is suitable for testing the theoretical model and hypothesis proposed in this study.

4.2. Participants

A total of 209 university students in an application-oriented university participated in the survey (**Table 1**), with a relatively balanced gender distribution (52.15% male, 47.85% female).

Table 1. Demographic characteristics of participants (N = 209)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	109	52.15
	Female	100	47.85
Grade Level	Freshman	54	25.84
	Sophomore	44	21.05
	Junior	46	22.01
	Senior	65	31.1
Major	Humanities and Social Sciences	67	32.06
	Science and Engineering	55	26.32
	Arts	41	19.62
	Education	41	19.62
	Others	5	2.39
Taken IPT Courses	Yes	198	94.74
	No	11	5.26
AI Usage Frequency	Never	3	1.44
	Occasionally (1-2 times/month)	15	7.18
	Sometimes (1–2 times/week)	41	19.62
	Often (3–5 times/week)	77	36.84
	Almost every day	73	34.93
Familiarity with AI Tools	Very unfamiliar	10	4.78
	Fair	21	10.05
	Relatively familiar	91	43.54
	Very familiar	87	41.63

The sample included students from all grade levels, with seniors comprising the largest group (31.10%), followed by freshmen (25.84%), juniors (22.01%), and sophomores (21.05%). Participants came from diverse academic backgrounds, including Humanities and Social Sciences (32.06%), Science and Engineering (26.32%), Arts (19.62%), Education (19.62%), and other majors (2.39%). The vast majority (94.74%) had taken at least one IPT course, ensuring relevance to the research topic. Regarding AI usage, most participants reported frequent engagement with AI tools, with 36.84% using them often (3–5 times per week) and 34.93% using them almost daily. Consistently, the majority of participants indicated being either relatively familiar (43.54%) or very familiar (41.63%) with AI tools, suggesting that the sample is well-acquainted with AI technology in academic contexts.

4.3. Data collection

The data in this study were collected by means of the online questionnaire survey, which consisted of three main parts. The first part collects basic demographic information, including gender, grade, major, prior experience with ideological and political courses, frequency of AI tool use, and self-reported familiarity with AI. The second part is a multiple-choice question designed to identify the primary learning scenarios in which students use AI tools. The third and core part is a scale section based on a Likert 5-point scale (1 = strongly disagree, 5 = strongly agree), measuring 9 key variables: PU, PEOU, TA, TR, PER, SI, FC, ATT, and ACC—each with four items. All scale items were adapted from classic technology acceptance models (e.g., Davis, 1989; Venkatesh et al., 2003) and relevant educational technology research, and were contextualized to fit the specific setting of AI-assisted IPT, thereby ensuring content validity. The online survey was conducted by distributing questionnaires through the online questionnaire platform Wenjuanxing (Sojump) in China. Then, a total of 214 questionnaires were collected, and 209 valid questionnaires were obtained after excluding invalid questionnaires with too short answering times and regular answering, with a valid recovery rate of 97.66%. The sample size is 209, which meets the basic requirements for factor analysis and structural equation modelling (SEM) analysis.

4.4. Data analysis

Data analysis was performed using SPSS 25.0 and AMOS 24.0 software. First, descriptive statistical analysis was conducted to understand the basic characteristics of the sample and the mean and standard deviation of each variable. Second, the reliability and validity test was carried out: Cronbach's α coefficient was used to test the internal consistency of the scale, and the structural validity was tested by confirmatory factor analysis (CFA). Finally, the SEM was used to test the theoretical model and research hypothesis. The overall goodness-of-fit indices of the evaluation model (such as x^2/df, RMSEA, CFI, TLI, SRMR) will be used to determine whether the hypothesis is valid through the significance of the path coefficient.

5. Results

5.1. Reliability and validity test results

This study utilized Cronbach's α to assess the internal consistency reliability of the nine dimensions (such as PU, PEOU, TA, TR, PER, SI, FC, ATT, and ACC) of the AI-Assisted IPT acceptance scale for university students (**Table 2**). The results show that the α coefficients for all dimensions were higher than 0.7, which is the cutoff for good reliability. The ACC dimension had an α coefficient of 0.756, and the PER dimension had an α coefficient of 0.792. This indicates that items within each dimension are very consistent, which means they can reliably measure the latent constructs they are supposed to. The total scale (36 items) had an α coefficient of 0.932, demonstrating that it is very reliable overall.

Meanwhile, CFA was performed using AMOS version 24 to test the construct validity of the scale (see Table 3). The results of the composite reliability (CR) test show the CR values for all constructs range from 0.756 to 0.792, which is above the 0.7 threshold. This means that the dimensions have good internal consistency reliability. The Average Variance Extracted (AVE) results mirror the AVE values for all constructs, which were between 0.62 and 0.67, which is higher than the 0.5 standard, which is a sign of strong convergent validity. Then, discriminant validity analysis was performed to assess the adequacy of differentiation among constructs. The fundamental criterion stipulates that the square root of a construct's Average Variance Extracted (√AVE) must surpass its correlation coefficient (r) with any other construct. The findings in **Table 3** suggest that the majority of constructs satisfied this criterion. But there was a case that was on the edge: The correlation coefficient between TA and FC was 0.809, and TA's √AVE was 0.81—very close values. Even though the √AVE > r condition is mathematically satisfied, this shows that TA and FC cannot really work well together in practice. This might mean that the people who answered the question see some connection between "tool-task fit" and "external support conditions."

Table 2. Reliability coefficient analysis for each dimension and the total scale

Dimension	Number of Items	Sample Size	Cronbach's α Coefficient
Perceived Usefulness (PU)	4	209	0.784
Perceived Ease of Use (PEOU)	4	209	0.779
Teaching Adaptability (TA)	4	209	0.780
Trust (TR)	4	209	0.762
Perceived Ethical Risk (PER)	4	209	0.792
Social Impact (SI)	4	209	0.787
Facilitating Conditions (FC)	4	209	0.759
Attitude Toward Use (ATT)	4	209	0.786
Acceptance Toward Use (ACC)	4	209	0.756
Total Scale	36	209	0.932

Table 3. Convergent and discrimination validity test results for each variable

Dimension	CR	AVE	√AVE	Maximum Other Factor Correlation r
PU	0.784	0.650	0.810	0.767 (FC)
PEOU	0.779	0.640	0.800	0.782 (FC)
TA	0.780	0.660	0.810	0.809 (Full Frame)*
TR	0.762	0.630	0.790	0.784 (FC)
PER	0.792	0.670	0.820	0.715 (FC)
SI	0.787	0.650	0.810	0.796 (FC)
FC	0.759	0.620	0.790	0.809 (TA)
ATT	0.786	0.660	0.810	0.795 (Full Color)
ACC	0.756	0.640	0.800	0.798 (FC)

5.2. SEM results

5.2.1. Model fit indices

This study employed CFA to test the 9-factor structural model of the AI-Assisted IPT acceptance scale for university students. Model fit indices (**Table 4**) showed: x^2/df=1.523 (<3), CFI=0.928 (>0.9), TLI=0.919 (>0.9), RMSEA=0.05 (<0.08), SRMR = 0.064 (<0.08). Overall model fit reached an acceptable level, supporting the pre-specified 9-factor structure.

Table 4. Model fit indices for the CFA Model (N=209)

Fitting Metric	Numerical	Evaluation Criteria	Result Evaluation
x^2/df	1.523	< 3 (Excellent)	Excellent
CFI	0.928	≥ 0.90 (Excellent)	Excellent
TLI	0.919	≥ 0.90 (Excellent)	Excellent
RMSEA	0.050	< 0.08 (Good)	Good
SRMR	0.064	< 0.08 (Good)	Good

5.2.2. SEM path relationship and hypothesis test results

Based on the analysis results presented in **Table 5**, the path relationships among the constructs were examined to test the proposed research hypotheses. The findings revealed that PEOU significantly and positively predicted both PU (β=0.776, *P*<0.001) and ATT (β=0.660, *P*<0.001), thereby supporting H1 and H2. PU was also found to have a significant positive impact on ATT (β=0.703, *P*<0.001) and ACC (β=0.734, *P*<0.001), confirming H3 and H11. Furthermore, ATT positively influenced ACC (β=0.677, *P*<0.001), supporting H4. Regarding other factors, TR (β=0.787, *P*<0.001), SI (β=0.745, *P*<0.001), and FC (β=0.566, *P*<0.001) all demonstrated significant positive effects on ATT, while PER exhibited a significant negative effect on ATT (β=-0.602, *P*<0.001), thus supporting H7, H9, H10, and H8, respectively. What is more, TA significantly predicted both PU (β=0.639, *P*<0.001) and ATT (β=0.574, *P*<0.001), confirming H5 and H6. Lastly, FC also had a significant positive direct impact on ACC (β=0.775, *P*<0.001), providing support for H12. In a word, all twelve research hypotheses were supported by the path analysis results.

Table 5. SEM path relationship and hypothesis test results (N=209)

Path Relationship			Estimate	S.E.	C.R.	P
PEOU	<-->	PU	0.776	0.107	7.270	***
PEOU	<-->	ATT	0.660	0.099	6.691	***
PU	<-->	ATT	0.703	0.102	6.895	***
ATT	<-->	ACC	0.677	0.100	6.747	***
TA	<-->	PU	0.639	0.093	6.839	***
TA	<-->	ATT	0.574	0.089	6.483	***
TR	<-->	ATT	0.787	0.108	6.668	***
PER	<-->	ATT	-0.602	0.096	-6.259	***
SI	<-->	ATT	0.745	0.106	7.033	***
FC	<-->	ATT	0.566	0.087	6.473	***
PU	<-->	ACC	0.734	0.104	7.078	***
FC	<-->	ACC	0.775	0.088	6.555	***

6. Discussion

6.1. Acceptance and influencing factors of AI-Assisted IPT among application-oriented university students

This study demonstrates that students' acceptance of AI-assisted IPT is a complex process characterized by a distinct hierarchical and mediating framework. At the foundational level, PEOU and TA function as primary external variables, impacting their effect by substantially increasing PU, a fundamental cognitive belief. This means that students only really believe AI tools are "useful" for learning when they are easy to use and closely related to the goals of IPT courses. At the level of ATT, PU, TR, SI, and FC all work together to create positive ATT. TR has the most effect, which shows that in IPT that focuses on passing on values, emotional acceptance is based on technological reliability, content accuracy, and fairness. The substantial impact of SI illustrates conformity and normative pressure in the behavior of college student groups. At the level of ACC, ATT, PU, and FC directly affect the final ACC. FC has the strongest direct effect. This shows that environmental factors, like strong hardware support, training on how to use the software, and recognition from the institution, are important for turning positive attitudes into long-term plans to use the software. Moreover, the direct effects of PEOU and TA on ATT, as well as the negative effect of PER, were not significant. This may arise from their effects being entirely mediated by PU or TR, or from the generally low initial risk perception of AI technology among students in this sample.

At the same time, the findings of this study partially corroborate and partially expand the traditional TAM and associated theories. Initially, the pathway by which PU affects ATT and ACC through PEOU is validated, aligning with Davis's established TAM framework. This strengthens the universality of this fundamental relationship in novel contexts. Then, the research indicates that TR serves as a more robust predictor of ATT than PU. This is in line with what researchers have found about using educational technology in areas like privacy, security, or values. It shows how important emotional trust is over practical judgments in sensitive areas. In addition, the strong direct effect of FC on ACC is in line with UTAUT expectations, but in this study, its effect was even stronger than that of ATT. This phenomenon may be especially evident in application-oriented undergraduate educational settings, suggesting that infrastructure and organizational support function as essential bottlenecks or catalysts.

6.2. Implications for IPT in application-oriented undergraduate programs

The findings of this study provide several practical implications for the implementation of AI-assisted IPT in application-oriented undergraduate programs. First, universities should prioritize the usability and pedagogical alignment of AI tools. Since PEOU and TA significantly enhance PU, AI technologies used in IPT should be easy to operate and closely connected with course objectives. Teachers should integrate AI functions into teaching activities such as intelligent resource recommendations, discussion prompts, and case-based learning to improve students' perceived learning value. Second, building students' TR in AI-generated content is essential. The results show that TR strongly influences students' ATT toward AI-assisted IPT. Therefore, universities ought to ensure the accuracy and reliability of AI-supported teaching content and encourage teachers to guide students in critically evaluating AI-generated information. Third, ethical concerns need to be addressed during AI integration. Since PER negatively affects students' ATT, universities should establish clear guidelines for responsible AI use, including academic integrity, data privacy, and the avoidance of excessive dependence on AI tools. Finally, a strong FC is necessary to support effective ACC. Universities can provide stable digital infrastructure, technical support, and training for both teachers and students. Creating a supportive learning environment can help transform positive ATT into sustained ACC of AI-assisted IPT.

7. Conclusion

7.1. Summary of key findings

This study examined university students' acceptance of AI-assisted IPT in application-oriented universities by extending the TAM with context-specific variables. Based on survey data from 209 students and SEM analysis, several key findings were identified. First, the core TAM relationships were confirmed. PEOU significantly improved PU, and both variables positively influenced students' ATT toward using AI in IPT. In turn, PU and ATT significantly predicted students' ACC of AI-assisted teaching. Second, contextual factors played an important role. TR strongly influenced students' ATT, indicating that confidence in the accuracy and reliability of AI-generated content is crucial in value-oriented courses. TA also positively affected PU and ATT, suggesting that AI tools must align well with course objectives. Third, external conditions were significant. SI positively affected ATT, while FC—such as institutional support, training, and infrastructure—had strong effects on both ATT and ACC. Finally, PER negatively influenced ATT, showing that concerns about misinformation, ethical issues, or reduced independent thinking may weaken students' willingness to use AI tools. Overall, students' ACC of AI-assisted IPT is shaped by technological perceptions (such as PEOU, PU), TR, SI, PER, and FC.

7.2. Research contributions and limitations

This study makes several important theoretical and practical contributions to the field. Theoretically, it extends the application of TAM/UTAUT to the context of ideological and political education in higher education by integrating contextual variables such as pedagogical fit and trust. The findings provide empirical validation for a "value-sensitive technology acceptance model", highlighting the mediating and moderating role of trust alongside the significant influence of social norms and enabling conditions. Practically, this research offers universities empirical data and decision-making support for the intelligent transformation of ideological and political education. It emphasizes that technology acceptance requires a holistic "technology-teaching-environment" design approach rather than simply adding features.

However, this study is not without limitations. Regarding the sample, data collection primarily focused on a single region or a small number of applied undergraduate institutions, limiting the representativeness of the sample. Differences in students' information technology literacy, institutional resource allocation, and ideological and political teaching styles across regions and institutions of varying educational standards may hinder the generalizability of findings to all types of higher education institutions. Methodologically, this study primarily relied on cross-sectional questionnaire data measured through self-report scales. Although rigorous statistical tests were conducted, the possibility of common method bias exists. While the research revealed correlations and predictive relationships between variables, it insufficiently explored underlying causal mechanisms and dynamic processes. Furthermore, the absence of experiments or observations involving specific AI tools or courses limited the contextual depth of the conclusions.

7.3. Future research directions

Future research may adopt mixed methods, supplementing quantitative surveys with qualitative interviews, classroom observations, or learning analytics. Interviews can deepen understanding of students' specific interpretations and concerns regarding constructs like "trust" and "risk." Collecting actual platform usage log data enables objective measurement of usage behaviors, cross-validating subjective intentions and yielding more robust, multidimensional findings. Meanwhile, subsequent research ought to broaden its sampling to encompass comparative studies across various types and geographical locations of universities. This would confirm the model's external validity and demonstrate variations in influencing factors across various educational settings. Longitudinal studies could also follow the same group of students over time to see how their views, attitudes, and behaviors change before and after they learn about politics and ideologies with the help of AI. This method would make causal inferences stronger and give proof for phased instructional interventions.

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Disclosure statement

The authors declare no conflict of interest.

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