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Large Language Model-Based Chatbots in Education: Student Perspectives on AI-Generated Text Quality and Credibility in Wuhan's Private Universities

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Abstract:
This paper examines how Large Language Model (LLM) chatbots are incorporated into Wuhan's private undergraduate education. It evaluates the dependability of AI-generated information using the Technology Acceptance Model (TAM) and emphasizes the significance of fostering critical thinking in Private Higher Education (PHE). The results point to a deficiency in critical thinking education as underclassmen appear to rely too much on chatbots. Less interaction with AI technologies is seen among arts students, which may indicate a mismatch with their creative requirements. The report criticizes China's PHE for its profit-driven strategy and poor faculty development, and it makes recommendations for changes that would encourage responsible AI use, protect educational rights, and encourage critical thinking.

Keywords:
Large Language Model, Private Higher Education, China, Critical Thinking, Technology cceptance Model, Student Rights

1.Introduction

The rapidly growing private higher education (PHE) market in China faces serious structural issues, such as profit-driven corporate strategies and limitations on faculty development. These problems restrict teachers' professional development in addition to impeding pupils' access to education. Consequently, there are benefits and drawbacks to using chatbots that are based on large language models (LLMs) in educational contexts. Emerging technologies that support educators with their teaching and give students individualized learning experiences include ChatGPT and ERNIE Bot. However, the dissemination of false or biased information by LLMs has the potential to lower academic standards and minimize the teacher's authority. The paper seeks to critically examine, from the viewpoint of students in Wuhan, China's private institutions, the usage of LLM-based chatbots as instructional tool. It investigates the factors driving these students' adoption of chatbots for academic work, their perceptions of the credibility of LLM-generated material, and the ethical considerations

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that follow. The research focuses in particular on how the use of chatbots in circumstances where systemic education issues may require changes that prioritize ethical use of technology and critical thinking.

2.Materials and Methods

There are 2,956 institutions in China's higher education system, including public and private. The autonomy and professionally oriented curriculum of independent colleges, which are private establishments associated with public universities, have contributed to their increasing popularity [1]. Students seeking individualized, diverse, and international education with a focus on professional growth and social responsibility are catered to by private institutions in China [2]. China's private education sector has grown dramatically since the 1980s; between 2001 and 2016, the number of private Higher Education Institutions (HEIs) increased from 39 to 786, with 6.3 million students. Even with a few enrollment drops, more growth is anticipated. These institutions' quality vary, nevertheless, and they frequently fall short of public HEIs. Public universities with ample funding are found in large cities like Beijing and Shanghai instead of Wuhan. These differences draw attention to the difficulties facing China's growing private education industry and set the stage for the use of chatbots with Large Language Models (LLMs) in education [3].

Conflicts arise when different internal and external stakeholders' goals and beliefs disagree in the context of higher education. These conflicts arise from a variety of interests, including management's financial efficiency goals [4], faculty members' career aspirations [5], and students' pursuit of accredited degrees [6]. Systemic problems in PHE, like conflicts with teaching quality assurance and student-institution fit, aggravate these disputes furthermore, emphasizing the need for innovation and change [7]. Meanwhile, the growing usage of chatbots for learning and creation is one of the new trends that is changing higher education. One of the newest and most well-liked chatbots, ChatGPT, can produce messages in a variety of subjects and styles, providing new opportunities for expression and instruction [8]. Nevertheless, ChatGPT also raises ethical questions for academics because the texts produced by AI could be prejudiced, inaccurate, or misleading, which could compromise their credibility. Furthermore, relying too much on ChatGPT might lead to bias [9], misinformation [10], plagiarism and cheating [11]. These universities deal with structural problems including profit-driven operations and limits on faculty growth, but they also specialize in vocational education and specific sectors that could benefit from LLM-based chatbots [7].

2.1 The Impact of AI Tools in Higher Education

AI (Artificial intelligence) has increasing applications in a variety of domains, including education. AI Endeavor (AIEd) is one of the most prominent and promising areas of technological innovation. AIEd research and practice encompass many major areas, including chatbots [12]; expert systems [13]; intelligent tutors or agents [14] that can provide learners with tailored, appropriate, and timely materials, guidance, and feedback; and machine learning [15]. Chatbots are computer programs that can simulate a natural language conversation with human users. Despite isolated innovations like PLATO [16], educational applications of early AI faced significant barriers to access and affordability for students and schools.

Eventually, the revolution phenomenon is the nonprofit technical company OpenAI released ChatGPT in November 2022. It is a generative AI-driven chatbot that surpasses previous AI learning tools by under-

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standing sophisticated human language and engaging in human-like discussions. They learn from enormous amounts of data using machine learning algorithms, providing unique and diverse outputs that fulfill user requirements [8]. OpenAI is prohibited from being used in China; nonetheless, Baidu's ERNIE Bot, a rival, claims to be able to answer Chinese inquiries more correctly. For teachers and students, the chatbot can offer new pathways for generating, expressing, and learning [17].

2.2 The Potential and Challenges of Large Language Model-Based Chatbots in Educational Settings

AI is finding its way into education through applications in flipped classrooms, blended learning, and massive open online courses. Rather than AI-generated material, these systems generally concentrate on settled content, such as uploaded files and online seminars [18]. There are issues about how accurate and dependable Large Language Model (LLM)-based chatbots are in producing educational material. Research suggests that even little changes to the input might have erratic results. Semantic inconsistencies, where LLM-based chatbots give contradictory responses for similar inputs or their own content, have also been demonstrated [19]. Notwithstanding these obstacles, LLM-based chatbots offer rapid, tailored response and hold great promise for education.

As more students look for individualized and engaged digital learning experiences, they can match their demands by offering quick, tailored feedback. LLM-based chatbots may be successfully integrated into education due to the IDEE framework, which also considers ethical considerations. As seen in Figure 1 [20], this method emphasizes the necessity of identifying explicit objectives, determining the appropriate level of automation, ensuring ethical usage, and monitoring efficacy. Teachers may get the most out of LLM-based chatbots and minimize over-reliance on their output by employing a systematic approach.

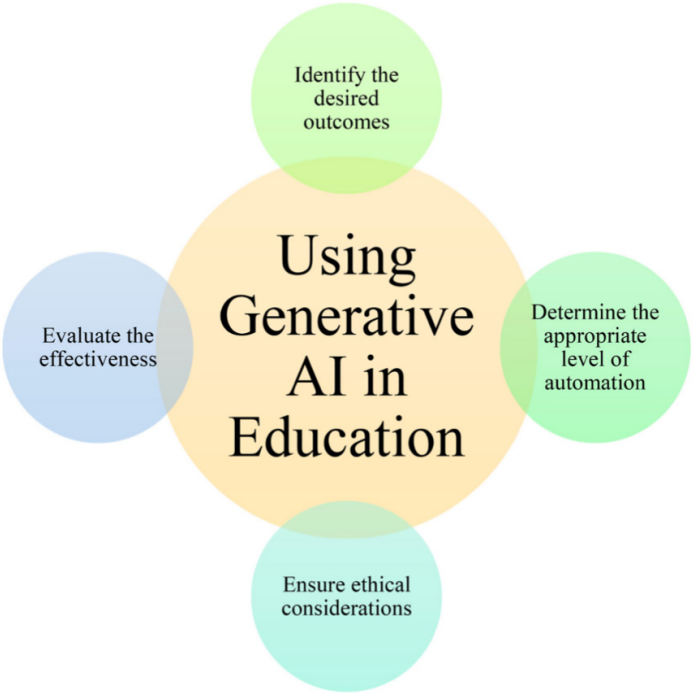


Figure 1 Theoretical framework for using generative AI in education

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2.3 The Awareness, Attitudes, and Usage of LLM-Based Chatbot Among Students

The impact of demographic characteristics on students' awareness and attitudes toward AI technology is highlighted by recent studies. In comparison to women and younger respondents, men and older respondents showed a greater comprehension of AI. Higher AI capability was demonstrated by those with CS and IT backgrounds [21]. The way in which students view and utilize LLM-based chatbots is influenced by their level of satisfaction with university support. Chatbots are more likely to be used by those who are dissatisfied with university help [22].

According to the Technology Acceptance Model (TAM), a technology's perceived utility (PU) and ease of use (PEOU) have a major impact on its acceptability [23]. Although LLM-based chatbots provide advantages, they also present ethical challenges, such as academic dishonesty and worries about biases, legal liability, and intellectual property [24]. Pupils question the authenticity and integrity of LLM's content, particularly in light of bias and false information [25]. These worries call for a careful strategy that weighs the advantages and the hazards of integrating AI in education [26].

2.4 Guidelines and Considerations for Educators and Policymakers in Private Higher Education

China's PHE industry has grown rapidly since the 1980s, but it still has difficulties with enrollment, quality, and control [1]. These establishments seek to offer individualized, varied, and global education with an emphasis on social responsibility and professional advancement [2]. However, they also have to deal with problems including overcrowding, lax entrance requirements [27], unscrupulous hiring procedures, and limited funding [28].

The lack of enthusiasm and involvement in research and intellectual pursuits among academic staff members is a serious concern; partially because their interests are not adequately protected [29]. Rapid increases in personnel levels and student enrollment have resulted in a drop in the caliber of hiring, a shortage of full-time employees, and worries about the caliber of education [30].

Policymakers and educators in China need to take several factors into account to improve PHE's sustainability and quality. Since many PHE instructors have fewer qualifications and fewer prospects for growth, professional development is essential for improving their efficacy as teachers [31]. While some educators use LLM-based chatbots creatively in the process of teaching [32], balanced guidance is needed to maintain academic integrity [33].

Teachers also have difficulties controlling student plagiarism and upholding academic rigor. For educators to make a good impact on their institutions, they must have systematic support and empowerment [34]. AI tools like LLM-based chatbots can function similarly to human educators and offer comprehensive feedback, raise concerns about replacing human educators and ethical dimensions of technology use [35].

A complicated policy framework that frequently lacks clarity and flexibility characterizes governance in China's PHE, which results in inefficiencies in serving the many requirements of institutions, students, and teachers [27]. To ensure effective governance and responsibility from all stakeholders, a more integrated strat-

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egy is needed.

2.5 Data Collection Methods

355 students took part in an online poll in a Wuhan private university study investigating the application of LLM-based chatbots in the classroom. The Technology Acceptance Model (TAM) served as the basis for the survey, which evaluated students' opinions on the utility and usability of chatbots. Convenience sampling was used to choose the participants, who were verified to be undergraduate students with prior chatbot usage experience by social media screening. The study employed a combination of quantitative and qualitative techniques, such as semi-structured interviews and an online survey, to obtain a thorough understanding of students' perspectives and encounters with chatbots in their assignments. Perceptions were measured using a 5-point Likert scale (Strongly Agree=5, Agree=4, Neutral=3, Disagree=2, Strongly Disagree=1), and control factors included gender, grade, and major. As the Table 1 shows, a significant Bartlett's test result and a KMO score of 0.837 supported the study's validity.

Table 1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.837
Bartlett's Test of Sphericity	Approx. Chi-Square	2467.113
	df	91
	Sig.	0.000

2.6 Applying the Technology Acceptance Model in Statistical Analysis

This paper was analysed using SPSS25.0 statistical software and the results were obtained as shown in the Table 2. From the results, the overall reliability of the questionnaire is 0.855, and the reliabilities of Satisfaction of Support Provided by University (SSPU), Perceived Usefulness of LLM-based chatbots (PU), Perceived Ease of Use of LLM-based chatbots (PEU) and Attitude towards Using (ATU) are 0.804, 0.871, 0.901 and 0.844 respectively.

Table 2 Reliability Statistics Cronbach's Alpha

Research variable	items	Cronbach's Alpha
SSPU	3	0.804
PU	4	0.871
PEU	4	0.901
ATU	3	0.844
total	14	0.855

From the data in the Table 3, it can be seen that all variable commonalities above 0.4, indicating minimal information loss and robust factor representation. Factor loadings exceeded 0.5 with no significant cross-loading, demonstrating clear factor clustering and strong reliability. The model's explained variance stood at 74.92%, well above the acceptable 60% threshold, affirming the structural validity of the constructs: PEU, PU, ATU, and SSPU within the study's framework.

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Table 3 Exploratory Factor Analysis with for Dimensions (principal components)

Factor Items		Factor Loadings				Communalities
		1	2	3	4	
SSPU	SSPU1				0.822	0.689
	SSPU2				0.839	0.751
	SSPU3				0.828	0.729
PU	PU1		0.784			0.666
	PU2		0.77			0.737
	PU3		0.886			0.837
	PU4		0.823			0.696
PEU	PEU1	0.847				0.752
	PEU2	0.827				0.699
	PEU3	0.896				0.825
	PEU4	0.895				0.814
ATU	ATU1			0.81		0.735
	ATU2			0.853		0.808
	ATU3			0.832		0.751
Initial Eigenvalues		4.916	2.480	1.750	1.343	-
Cumulative %		35.11%	52.83%	65.33%	74.92%	-

From the Table 4 below, it can be seen that validity testing indicated a good model fit, with CMIN/DF at 1.653, GFI and AGFI at 0.8, TLI, IFI, and CFI at 0.9, RMSEA at 0.045, and both PGFI and PNFI greater than 0.5, all meeting general SEM study criteria (Hu & Bentler, 1995).

Table 4 Fit Indices for Measurement

Goodness-of-fit measure	Acceptable Values	Model Values
CMIN		119.023
DF		72
CMIN/DF	<3	1.653
GFI	>0.8	0.950
AGFI	>0.8	0.927
RMSEA	<0.08	0.045
IFI	>0.9	0.981
TLI	>0.9	0.975
CFI	>0.9	0.981
PGFI	>0.5	0.651
PNFI	>0.5	0.754

This hypothesis is grounded in the assumption that a lack of university support, particularly in fostering critical thinking skills, might drive students towards more LLM-based chatbots as a substitute for traditional academic support. The questionnaire was designed to capture this dynamic, exploring how students' perceptions of insufficient support from their university might affect their attitudes and usage behaviors towards LLM-based chatbots. In the SEM (Structural Equation Modelling) Figure 2, students' satisfaction with university support is negatively linked to their Perceived Usefulness (PU) and Perceived Ease of Use (PEU) of LLM-based chatbots. This negative relationship hypothesizes that dissatisfaction or a sense of lack in university support systems could lead to a heightened perception of LLM-based chatbots as a useful and easy-to-use tool, compensating for the perceived educational gaps.

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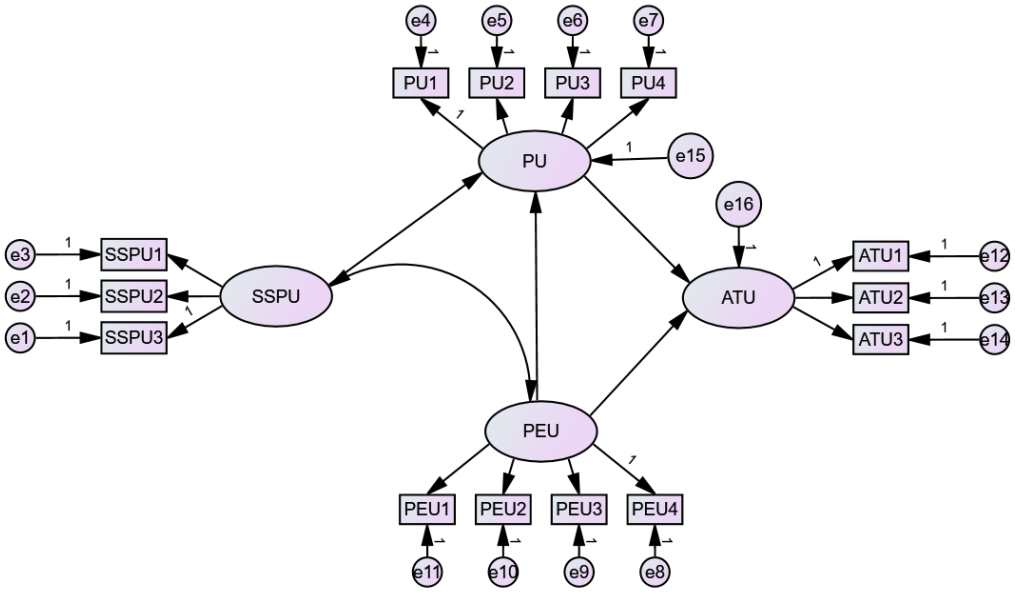


Figure 2 Path Diagram of the Initial Structural Equation Modelling

This insight leads to a critical discussion point: to effectively integrate LLM-based chatbots into the educational process, private universities must invest in training their teachers. This training is essential for educators to develop a deeper understanding of AI tools, enabling them to guide students more effectively in their academic pursuits. Importantly, this means allocating sufficient time and resources to allow teachers to engage in such training. By doing so, universities will not only enhance the quality of education but also equip both students and faculty with the necessary skills to navigate and leverage AI technologies responsibly and effectively in the academic sphere.

The following Table 5 presents path coefficients with factor loadings ranging from 0.687 to 0.907, surpassing the 0.5 threshold. Measurement errors are non-negative with small standard errors, and critical ratios (C.R.) exceed 3.29, indicating strong explanatory power and good model fit, as evidenced by significance at the 0.001 level (***). Reliability scores for variable components range from 0.806 to 0.901, and average variance extracted values from 0.582 to 0.696, all above the 0.7 and 0.5 benchmarks, respectively, confirming convergent validity. The model's dimensionality and fit are thus validated and deemed scientifically sound.

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Table 5 Path Coefficients of The Measurement Model

Satisfaction with University Support (SSPU)	Std. Estimate	CR	AVE
Overall satisfaction with the university's academic support.	0.687	0.806	0.582
Alignment of university's academic support with personal educational needs.	0.82		
Effectiveness of university's academic support in aiding coursework completion.	0.775		
Perceived Usefulness of LLM-based chatbots (PU)			
Utility of LLM-based chatbots compared to university resources.	0.722	0.875	0.639
LLM-based chatbot's role in the efficient completion of academic tasks.	0.81		
Contribution of LLM-based chatbots to coursework quality.	0.907		
Information accessibility through LLM-based chatbots.	0.745		
Perceived Ease of Use of LLM-based chatbots (PEU)			
Ease of learning how to use LLM-based chatbots.	0.792	0.901	0.696
LLM-based chatbot's ability to provide accurate information.	0.737		
User-friendliness of interacting with LLM-based chatbots.	0.907		
Ease of becoming skilled in using LLM-based chatbots.	0.889		
Attitudes Toward Using LLM-based chatbots (ATU)			
Intention to use LLM-based chatbots regularly for coursework.	0.764	0.848	0.65
Enjoyment of using LLM-based chatbots in coursework.	0.867		
Utility of LLM-based chatbots for overcoming obstacles in courses.	0.785		

3. Result and Discussion

3.1 Findings from Close-ended Questions Feedback

As Table 6 shown, the participant demographic is predominantly male (56.53%) and female (43.47%), with the majority being fourth-year students (28.57%), followed by third year (26.44%), second year (20.97%), and first year (24.01%). and distributed across majors, with Science (36.17%) being the most common, followed by IT (22.80%), Arts (20.97%), and Business (20.06%).

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Table 6 Demographic Breakdown of Survey Participants by Gender, Grade Level, and Major

Grade	n	%	Gender	n	%	Major	n	%
1 (Year 1)	79	24.01%	0 (Male)	186	56.53%	1 (Science)	119	36.17%
2 (Year 2)	69	20.97%	1 (Female)	143	43.47%	2 (IT)	75	22.80%
3 (Year 3)	87	26.44%				3 (Business)	66	20.06%
4 (Year 4)	94	28.57%				4 (Arts)	69	20.97%
Total	**329**	**100.00%**	**Total**	**329**	**100.00%**	**Total**	**329**	**100.00%**

Table 7 displays correlation coefficients between variables ranging from 0.201 to 0.532, and AVE values from 0.763 to 0.834, indicating adequate discriminant validity for the research variables.

Table 7 Pearson and Sqr.AVE

	SSPU	PU	PEU	ATU
SSPU	**0.763**			
PU	0.346	**0.799**		
PEU	0.201	0.251	**0.834**	
ATU	0.201	0.532	0.273	**0.806**

Figure 3 is the final model that shows the results of the direct effect value between variables. The relationship between the direct and the indirect effect will be explained in the subsequent explanation.

Figure 3 Final Path Diagram of The Measurement Model

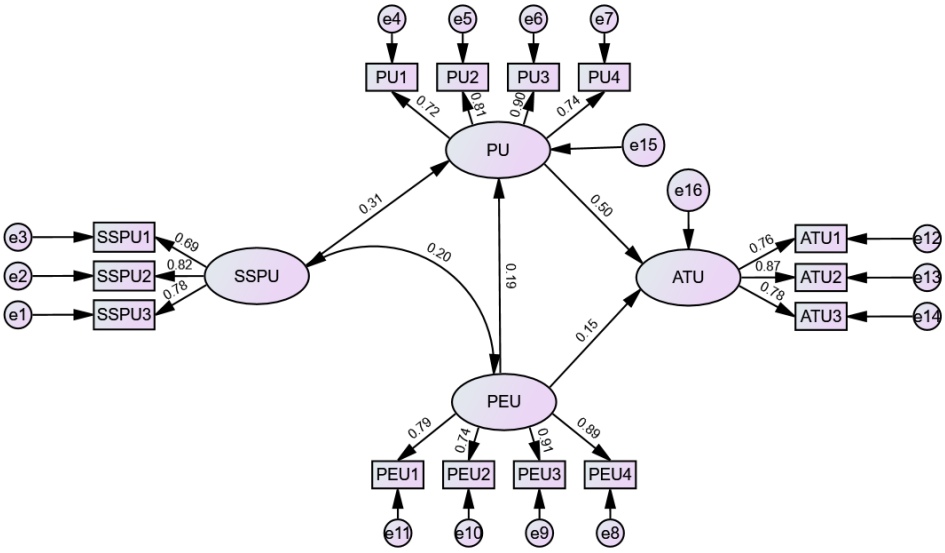


Table 8's SEM results reveal significant positive effects: SSPU and PEU on PU ($p < 0.05$; coefficients 0.308, 0.189), and PU and PEU on ATU ($p < 0.05$; coefficients 0.495, 0.149).

Table 8 Path Coefficient Estimation Table for Structural Equation Modelling

			Unstandardised coefficient	Standardised coefficient	S.E.	C.R.	P
PU	<---	SSPU	0.382	0.308	0.082	4.654	<0.001
PU	<---	PEU	0.138	0.189	0.044	3.165	0.002
ATU	<---	PU	0.619	0.495	0.084	7.341	<0.001
ATU	<---	PEU	0.136	0.149	0.052	2.604	0.009

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The findings detailed in Table 9 reveal significant variances in student perceptions by academic year ($p<0.05$), with notable differences in SSPU ($F=9.489$), PU ($F=10.120$), PEU ($F=5.159$), and ATU ($F=14.042$). An inverse relationship exists between SSPU and ATU. Interestingly, as students advance in their academic years, their PU, PEU, and ATU tend to become more critical or negative. This suggests that students' increasing familiarity with the educational system and its support mechanisms may lead to a more discerning view of LLM-based chatbots.

Table 9 Analysis of Variance (ANOVA): Q1 Year

	year(M±SD)				*F*	*p*	LSD
	1.0(*n*=119)	2.0(*n*=75)	3.0(*n*=66)	4.0(*n*=69)			
SSPU	3.05±0.68	2.69±0.57	2.67±0.58	2.66±0.60	9.489	0.000**	1>2,1>3,1>4
PU	3.53±0.86	3.14±0.82	2.98±0.69	2.99±0.72	10.12	0.000**	1>2,1>3,1>4
PEU	3.69±0.93	3.64±0.87	3.46±0.97	3.16±0.99	5.159	0.002**	1>4,2>4
ATU	3.73±0.97	3.20±1.02	2.99±0.93	2.91±0.91	14.042	0.000**	1>2,1>3,1>4

Note. $p<0.05$ ** $p<0.01$

The data shows significant differences ($p<0.05$) in perceptions of LLM-based chatbots across Science, IT, Business, and Arts majors. Table 10 reveals highly significant variances ($p<0.01$) in all variables, with ATU showing the highest F-value (14.042), followed by PU (10.120), SSPU (9.489), and PEU (5.159). These variances likely arise from each major's unique academic requirements and expectations.

Table 10 Analysis of Variance (ANOVA): Q2 Major

	major(M±SD)				*F*	*p*	LSD
	Science (*n*=79)	IT (*n*=69)	Business (*n*=87)	Arts (*n*=94)			
SSPU	2.55±0.61	2.75±0.49	2.88±0.60	3.01±0.74	8.269	0.000**	2>1,3>1,4>1,4>2
PU	2.97±0.74	3.08±0.71	3.33±0.88	3.41±0.85	5.451	0.001**	3>1,4>1,4>2
PEU	3.32±1.05	3.38±0.95	3.48±0.99	3.83±0.77	5.222	0.002**	4>1,4>2,4>3
ATU	3.00±1.07	3.27±1.01	3.38±0.99	3.46±0.97	3.309	0.020*	3>1,4>1

Note. $p<0.05$ ** $p<0.01$

Contrary to the variations observed across different majors, Table 11 shows gender differences do not demonstrate statistical significance ($p>0.05$) for SSPU, PU, PEU, or ATU. This outcome indicates a uniformity in perceptions and attitudes towards LLM-based chatbots across gender lines, suggesting that male and female students share similar views and experiences regarding the use of this AI tool in their academic endeavors.

Table 11 Analysis of Variance (ANOVA): Q3 Gender

	gender(M±SD)		t	p
	male(n=186)	female(n=143)		
SSPU	2.84±0.67	2.77±0.61	1.017	0.310
PU	3.22±0.84	3.21±0.80	0.116	0.908
PEU	3.54±0.88	3.50±1.05	0.378	0.706
ATU	3.34±1.02	3.22±1.02	1.074	0.284

Note. p<0.05 ** p<0.01

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3.2 Findings from Open- ended Questions Feedback

Analysis of open-ended responses from 31 students reveals prevailing themes regarding LLM-based chatbot's promise and perils in Chinese private higher education. As shown in Table 12, when asked how LLM-based chatbots aid learning, the most common benefit cited was improved productivity (45%, n=14), followed by inspirational value (39%, n=12). As one student explained, LLM-based chatbots serve as the "best helper" for efficiently gathering information. However, 12 students (39%) also expressed accuracy and reliability concerns, while 9 (29%) warned of risks to academic integrity like plagiarism. Despite recognizing helpful capacities, students harbor significant doubts regarding the quality and ethics of AI-generated text.

Ambivalent perspectives were also evident regarding LLM-based chatbots integration in education. While 25% (n=8) noted benefits like personalized learning, an equal portion opposed integration altogether. Main reasons were diminished critical thinking and originality (13%, n=4), promoting laziness (10%, n=3), and ethical considerations (10%, n=3). As one student explained, "Students will not have subject competence or motivation to validate if relying completely on LLM-based chatbots." Others suggested usage requires proper guidance to avoid inappropriate dependency. In summary, while acknowledging useful applications, students hold reservations regarding the systematic integration of LLM-based chatbots in Chinese education.

Table 12 Thematic analysis of open-ended survey (Q18, 19 & 20)

Theme	n	%	Question
Improved Productivity	14	45.16%	18. How has using LLM-based chatbots facilitated or hindered your learning experience?
Inspiration and Guidance	12	38.71%	
Language Proficiency Improvement	2	6.45%	
Uncertainty	3	9.68%	
Accuracy and Reliability Concerns	12	38.71%	19. What challenges, risks, or ethical considerations have you encountered in using LLM-based chatbots for educational purposes?
Plagiarism and Academic Integrity	9	29.03%	
Over-reliance and Diminished Skills	4	12.90%	
Leakage of Information	2	6.45%	
Uncertainty	4	12.90%	
Empowering Personalized Learning	8	25.81%	20. What are the strengths and weaknesses of integrating AI tools like LLM-based chatbots into the education system?
Improving Productivity	6	19.35%	
Support with no reason	4	12.90%	
Promoting Laziness	3	9.68%	
Ethical Considerations	3	9.68%	
Reducing Originality	2	6.45%	
Enhancing Creativity	2	6.45%	

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3.3 Interpretation of Key Findings

The results showed that these perceptions varied significantly depending on the academic year and degree, but there were no discernible changes based on gender. In particular, we investigate how students' perceptions of AI tools such as LLM-based chatbots relate to their level of satisfaction with university help. Understanding how AI integration may improve or augment conventional teaching techniques requires knowledge of this analysis. Our goal is to analyze these results and provide guidance on how AI might be successfully incorporated into educational settings, considering both the advantages and disadvantages it brings.

The study provides a unique perspective by identifying subtle characteristics, such as major, year of study, and level of satisfaction with university support, that affect how LLM-based chatbots are used by students at private universities. The necessity for specialized teaching strategies at various academic levels is highlighted by the possibility that first- and second-year students may need greater assistance while utilizing LLM-based chatbots. Other than that, gender doesn't appear to have a big impact on these opinions. It reveals the importance of how AI technologies, such as LLM-based chatbots, contribute to academic integrity and ethical issues when students write academic papers in the initial stage [36].

Students who are dissatisfied with university support may think AI technologies are more helpful, as seen by the inverse association between their impressions of LLM-based chatbots and their level of satisfaction. The threats to content security posed by generative AI products are significant. These risks may be particularly relevant in an academic setting, especially if students increasingly rely on AI tools due to insufficient support from their universities [37].

A paper observation further enhance the conversation about how academic support affects students' dependence on AI technologies [32]. They relate to our findings on students' different dependence on AI tools dependent on their satisfaction with university support, emphasizing the need for improved digital literacy and ethical concerns in the integration of AI in university teaching and research administrationt.

3.4 Implications of AI Integration in Education

The integration of AI tools like LLM-based chatbots in education, particularly in private higher education (PHE), necessitates a multifaceted approach that enhances critical awareness, develops technical abilities, and nurtures human uniqueness.

A diverse strategy is required to help students develop critical awareness, which includes digital literacy, avoiding plagiarism, and encouraging independence. The function of LLM-based chatbots in meeting academic paper creation transparency requirements [36]. This shows that an educational system that encourages the moral use of LLM-based chatbots and their open acknowledgment in academic work is necessary. Furthermore, the attention to the risks of inaccurate information created by AI technologies [37]. Regular seminars and discussion forums where instructors and students interact with AI ethical specialists might be held at universities. These sessions might include talks on creating an ethical code for the use of AI tools in academic contexts, case studies of AI misuse, and debates on AI in education. A course may also cover topics like recognizing biases in AI outputs, comprehending the limitations of AI in academic research, and doing hands-on exercises where students compare and contrast articles produced by AI and humans.

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It is essential to bridge the skills gap in technical areas such as software, hardware, and academic writing, AI course content should be customized to meet the demands of individual professionals. To address domain-specific issues, it recommends changing the curriculum of AI courses to place more emphasis on proper application than on technical concept delivery. AI technology should be integrated with professional area information. Furthermore, the necessity of developing digital literacy to effectively use AI, pointing to the necessity of AI-focused curricula that advance students' digital abilities in data collection, processing, integration, and judgment [29]. A professional development program where instructors take part in practical seminars to learn how to employ AI tools like LLM-based chatbots, like utilizing chatbots for grading assignments and incorporating AI-generated content into lesson plans.

Enhancing instructors' and students' autonomy and creativity is one way to foster human qualities like empathy, collaboration, and innovation [30]. This may be accomplished by developing new practical exercises and teaching methods, which will foster skills like critical thinking and learning, in order to pique students' attention and have an illuminating and directing influence on professional applications, case content ought to be strongly connected to professional practice. A university may, for instance, host hackathons where students collaborate with one another and with AI technologies to tackle real-world issues in teams. An alternative strategy would be to incorporate humanities and arts into STEM classes in order to provide a more comprehensive education that emphasizes the importance of technology competency but also human understanding. With the exception of the fact that institutions may employ AI to offer teachers and students individualized services [30]. An AI system may be created, for example, to help professors find pertinent grant opportunities and research trends or to provide customized career advice based on students' academic achievements and interests.

3.5 Limitations and recommendations for future research

The study examining Chinese private university students' use of LLM-based chatbots reveals important insights but has certain limitations. The findings' wider relevance may be restricted by its convenience sampling strategy and concentration on private colleges in China. The usage of Excel and SPSS may not capture complicated data details, and the questionnaire-based technique may induce biases. Also, the study's design leaves out faculty viewpoints and prohibits concluding causality. Notwithstanding these limitations, it opens new avenues for investigation, including strong sampling, mixed techniques, sophisticated analysis, long-term studies, moral concerns, faculty feedback, and policy analysis to improve AI-enabled education worldwide.

4.Conclusion

The use of LLM-based chatbots in China's Private Higher Education is bringing out both benefits and major obstacles. This study provides insight into PHE students' ethical perceptions of and interactions with AI technologies, demonstrating a complex link that goes beyond simple technological issues. Comprehensive changes in both curricular material and instructional techniques are required to successfully execute the strategies described. Strong institutional commitment to ethical AI usage, including well-defined policies, moral benchmarks, and ongoing professional development for teachers to stay up to date with AI developments in education, should serve as the foundation for these reforms. The results of this study provide crucial direction

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for educators, policymakers, and educational institutions in utilizing technology advantages responsibly as AI changes educational paradigms. The report promotes swift, extensive changes to China's PHE system in order to guarantee that teaching methods are not only creative but also fair and adaptable, protecting the interests of educators and students as a whole.

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