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Conflicting AI Explanations and Trust Dilemma: A Study on Students' Interpretation and Choices Among Multiple AI Tools

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Abstract:

Artificial intelligence (AI) has become an important learning tool in education. Students frequently use AI platforms such as ChatGPT, Google Gemini, Claude and Perplexity AI to clarify doubts, complete assignments, prepare for exams and receive research support. However, different AI tools sometimes give different answers for the same question. This creates confusion among students. It also affects their trust in AI-generated information. This study examines how students interpret conflicting AI responses and how these differences influence their trust, verification behaviour, critical thinking and decision-making. The study is based on primary data collected from 244 students from different universities in Odisha. Both technical and non-technical students were included in the study. The collected data were analysed using Percentage analysis, Reliability analysis (Cronbach's Alpha), KMO and Bartlett's Test, Factor Analysis, Pearson Correlation Analysis and Chi-Square Test. The findings show that ChatGPT is the most used AI tool among students. Many students use more than one AI tool at the same time. Students mainly trust AI answers that are clear, logical and easy to understand. Many students compare different AI responses before accepting an answer. Some students also verify information using textbooks or trusted online sources. The study also found that conflicting AI answers improve critical thinking and evaluation skills. At the same time, they also reduce trust and create confusion. The study concluded that AI tools are useful for education, but students should use them carefully. However, contradictory outputs also reduce trust and create uncertainty during academic decision-making. Many students prefer to combine multiple AI responses before forming their final understanding of a topic.

Keywords — **Artificial Intelligence, Trust, Education, AI Outputs, Generative AI, Odisha**

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I. INTRODUCTION

Artificial intelligence (AI) has significantly transformed the educational environment in recent years. The rapid development of generative AI systems such as ChatGPT (Chat Generative Pre-trained Transformer), Google Gemini and Perplexity AI has changed how students access information, complete assignments, prepare for examinations and solve academic problems. These AI systems provide immediate responses and personalised explanations, making them highly attractive learning tools for students **(Fathi et al., 2025; Jauhiainen & Guerra 2024).** The integration of AI into education has increased because of its ability to simplify complex academic tasks and improve learning efficiency. Students frequently use AI tools for summarising content, generating ideas, coding assistance, research support and doubt clarification. The convenience and speed offered by AI platforms have made them a regular part of students' academic routines **(Adewale et al., 2024; Naseer et al., 2024; Schei et al., 2024).**

However, despite their usefulness, generative AI tools also present several challenges. One major issue is the occurrence of conflicting or contradictory outputs generated by different AI systems for the same question. Since AI models are trained using different datasets, algorithms and response-generation mechanisms, their explanations may vary significantly. In many cases, one AI tool may provide a completely different interpretation compared to another tool. Such contradictions create confusion among students and raise concerns regarding reliability and trustworthiness **(Lee et al., 2024**). Another major challenge is that AI systems often generate highly confident but inaccurate information, commonly referred to as "*AI hallucinations*." Students who lack strong verification skills may accept incorrect information without proper evaluation. This situation becomes more problematic when students use multiple AI tools simultaneously and receive inconsistent academic explanations **(Danyaro et al., 2025).** Trust, therefore, becomes a crucial factor in AI-assisted learning. Students often decide which AI response to trust based on clarity, familiarity, logical consistency, or ease of understanding rather than factual accuracy. Some students verify information using textbooks, teachers, or credible online sources, while others combine multiple AI responses to create their own understanding of the topic **(Abuzar et al., 2025).** The growing dependence on AI tools in education makes it important to understand how students interpret conflicting AI outputs and how such conflicts influence trust and decision-making behaviour. This study attempts to examine the opportunities and challenges associated with the use of multiple AI tools among students. It also investigates how students react when AI systems provide contradictory information and what strategies they adopt to verify and evaluate AI-generated content.

The study contributes to the growing field of educational technology and AI-assisted learning by identifying student trust behaviour, verification practices and decision-making patterns in situations involving conflicting AI explanations.

II. LITERATURE REVIEW

1. AI Adoption and Usage in Education

AI helps students learn in a better and more personal way. Intelligent tutoring systems and adaptive learning platforms adjust lessons according to each student's needs and learning speed. This improves student interest, performance and memory **(Abbas et al., 2023; Chen et al., 2020; Kamalov et al., 2023; Onesi-Ozigagun et al., 2024).** In language and medical education, AI tools such as chatbots, writing feedback systems and simulations help students practice skills, make decisions and learn independently **(Banjade et al., 2024; Roveta et al., 2025; Son et al., 2023; Sriram et al., 2025).** AI is also useful in administration. It helps with grading, enrollment, scheduling and resource management. This saves time and allows teachers to focus more on teaching and student interaction **(Chan & Tsi, 2023; Kuleto et al., 2021).** Most studies agree that AI cannot replace human teachers. Teachers provide emotional support, understanding, motivation and personal guidance that technology cannot fully offer **(Adel, 2024; Francis et al., 2025; Xiao et al., 2025).** AI works best as a supportive tool that helps teachers rather than replacing them. Researchers also suggest the need for strong ethical guidelines to ensure the safe and responsible use of AI in education. In higher education, institutions should also develop clear best-practice models for the proper use of Generative AI tools **(Bahroun et al., 2023; Banjade et al. 2024; Cordero et al., 2025).**

2. Trust And Reliability of AI Systems

Trust and reliability in AI are closely related, but they are not the same. AI systems must be reliable and technically trustworthy. At the same time, people must develop a balanced level of trust in AI. Researchers explain that trustworthy AI should be safe, accurate, fair, transparent, secure and easy to understand. It should also protect privacy, reduce errors and include human supervision throughout its use **(Alzubaidi et al., 2023; Kaur et al., 2022; Li et al., 2021; Rodríguez et al., 2023).** Reliability means that the AI gives correct and consistent results. This is an important factor in building trust **(Afroogh et al., 2024; Alzubaidi et al., 2023).** Studies also show that trust in AI depends not only on technical quality but also on user experience, social values and personal attitudes. Some people trust AI too much, while others do not trust it at all. Therefore, trust should be properly balanced **(Li et al., 2024; Okamura & Yamada, 2020; Ferrario, 2024; Bach et al., 2022).** Research on human-AI interaction shows that people often depend too much on AI advice simply because it is machine-generated, even when the advice may be incorrect. This can lead to poor decisions **(Okamura & Yamada, 2020; Ingram, 2023).** To improve trust, researchers suggest using clear explanations, confidence indicators and trust-calibration methods. However, their effectiveness can vary depending on the situation and task **(Durán & Pozzi, 2025; Jacovi et al., 2020; Tutul et al., 2024).** Some philosophers argue that people should not treat AI like a human. Instead of "trusting" AI emotionally, it is better to rely on it carefully and responsibly. They also emphasise that the final responsibility always belongs to human developers, users and policymakers, not the AI system itself **(Durán & Pozzi, 2025; Li et al., 2021; Cao & Huang, 2022; Ryan, 2020).**

3. Critical Thinking and Verification

Critical thinking in AI use means carefully checking AI-generated information instead of accepting it immediately. It includes verifying sources, understanding how AI tools work and recognising their limitations. Research shows that people with stronger critical-thinking skills are more likely to use different verification methods. These methods include checking links, searching for information online and comparing answers with other tools or sources. They are also better at identifying true and false information **(Lau et al., 2025).** In education, researchers recommend teaching fact-checking techniques, information literacy and healthy skepticism. Methods such as lateral reading and SIFT help students evaluate AI-generated content more carefully and avoid being misled by AI "hallucinations" or incorrect information **(Li, 2025; Holzmann et al., 2025).** Studies also warn that excessive dependence on AI can reduce independent thinking. Many users may trust AI outputs too easily and stop verifying information. This can lead to over-reliance and weaker critical-thinking ability **(Gerlich, 2025; Zhai et al., 2024; Lee et al., 2025).** AI literacy also plays an important role. Understanding how AI systems and large language models work can encourage users to verify information more often. However, too much confidence in AI systems may reduce fact-checking because users start believing the information automatically **(Rheu & Cho 2025).** Overall, research highlights the importance of developing critical-thinking skills, verification habits and proper educational methods so that users remain active and careful evaluators of AI-generated content.

4. AI and Ethical Concerns

AI is growing quickly in many fields like healthcare, sports, city planning and finance. Along with its benefits, AI also creates many ethical concerns. The main issues are bias, lack of transparency, privacy risks and accountability **(Čartolovni et al., 2022; Hanna et al., 2024; Kim et al., 2025; Weiner et al., 2024).** One major problem is bias in AI systems. AI learns from data and if the data is unfair or incomplete, the results can also become unfair. Sometimes AI systems repeat stereotypes or discriminate against certain groups of people. This can happen in areas like medical treatment, hiring, banking, or public services **(Al-kfairy et al., 2024; Ferrara, 2024; Sanchez et al., 2025).** Another concern is transparency. Many AI systems work like a "black box." People cannot clearly understand how the AI made a decision. This reduces trust in AI, especially in important areas such as healthcare or government services. If people do not understand the reason behind a decision, it becomes difficult to question or correct it **(Cheong, 2024).** Privacy is also an important issue. AI systems collect and use huge amounts of personal data. This creates risks related to data misuse, surveillance and loss of confidentiality. People may also worry about whether their information is being used with proper consent **(Hanna et al., 2024).** Accountability is another challenge. When an AI system makes a mistake, it is often unclear who is responsible. The responsibility may fall on developers, companies, institutions, or users. This creates legal and ethical confusion **(Moch, 2024).** To reduce these problems, experts suggest strong AI rules and ethical practices. Ethical values should be included while designing AI systems. Fair algorithms, regular monitoring, diverse data and clear regulations can help make AI safer and more trustworthy. Cooperation between governments, researchers, industries and society is also important to ensure that AI benefits everyone fairly **(Radanliev, 2025; Rodríguez et al., 2023).**

Research Gap

Previous studies have explained the benefits and problems of AI in education. Most studies focused on single AI tools and their role in learning, teaching and administration. However, very few studies examined how students use multiple AI tools together for study purposes. There is also limited research on the opportunities and challenges students face while using these tools in real situations. Many studies discussed trust, reliability and ethical issues, but very little attention has been given to how students react when different AI tools give different or conflicting answers. It is still not clear how students decide which answer is correct, how they verify information and how critical thinking helps them in such situations. Therefore, this study tries to fill these gaps by studying the use of multiple AI tools among students, the opportunities and challenges they face and their responses to conflicting AI-generated outputs.

III. OBJECTIVES OF THE STUDY

1. To study the usage of multiple AI tools among students.
2. To identify opportunities and challenges faced while using AI tools.
3. To analyse student responses to conflicting AI-generated outputs.

IV. HYPOTHESES OF THE STUDY

H1: There is a significant relationship between confusion arising from conflicting AI outputs and reduction in trust toward AI-generated content.

H2: There is a significant relationship between logical evaluation of AI responses and cross-checking behaviour among students.

H3: Students using multiple AI tools demonstrate higher critical evaluation behaviour toward AI-generated content.

H4: Conflicting AI outputs significantly influence students' verification and decision-making behaviour.

V. METHODOLOGY

The study adopted a descriptive and analytical research design to examine students' trust behaviour and interpretation of conflicting AI-generated outputs. A quantitative research approach was used for collecting and analysing the data. The study was based on primary data collected through a structured questionnaire distributed among students from different universities in Odisha. The questionnaire included closed-ended statements measured using a five-point Likert scale ranging from Strongly Disagree (SD) to Strongly Agree (SA). Data were collected from 244 respondents belonging to Higher Secondary, Undergraduate, Postgraduate and Research Scholar categories. Both technical and non-technical students were included to ensure diversity in the sample. Convenience sampling technique was adopted for selecting the respondents because of accessibility and availability of participants. The collected data were analysed using Percentage analysis, Reliability analysis (Cronbach's Alpha), KMO and Bartlett's Test, Factor Analysis, Pearson Correlation Analysis and Chi-Square Test. SPSS 20 and Microsoft Excel were used for data analysis and interpretation.

VI. DATA ANALYSIS

Table 1: Demographic Profile of the Respondents

Description	Frequency	Percentage
Gender		
Male	118	48.4
Female	126	51.6
Total	**244**	**100.0**
Age		
15 – 18	3	1.2
19 – 21	127	52.0
22 – 25	94	38.5
26 and above	20	8.2

Total	**244**	**100.0**
Education		
Higher secondary	3	1.2
Undergraduate	117	48.0
Postgraduate	111	45.5
Research scholar	13	5.3
Total	244	100.0
Soft Skills		
Technical	131	53.7
Non- Technical	113	46.3
Total	**244**	**100.0**

Sources: Compiled from Primary Study

Table 1 demographic analysis indicates balanced participation from male and female respondents. Most respondents belonged to the 19–21 years age group and were undergraduate or postgraduate students. Technical students slightly outnumbered non-technical students, ensuring representation from diverse academic backgrounds.

Objective 1: To study the usage of multiple AI tools among students.

Table 2: Usage of multiple AI tools

Category	Frequency	Percentage
Most Preferred AI Tools		
ChatGPT	105	43.0
ChatGPT + Google Gemini	66	27.0
ChatGPT + Google Gemini + Claude	20	8.2
ChatGPT + Google Gemini + Perplexity AI	11	4.5
Other Combinations	42	17.3
Total	**244**	**100.0**
Frequency of AI Usage		
Daily	113	46.3
Several Times a Week	106	43.4
Rarely	18	7.4
Once a Week	7	2.9
Total	**244**	**100.0**
Purpose of AI Usage		
Doubt Clarification	67	27.5
Exam Preparation	54	22.1
Assignments & Homework	46	18.9
Research & Projects	46	18.9
Creative Writing	10	4.1
Multiple Purposes	21	8.5
Total	**244**	**100.0**
Number of AI Tools Used Simultaneously		
Only 1 Tool	92	37.7
2–3 Tools	120	49.2
More than 3 Tools	32	13.1
Total	**244**	**100**

Sources: Compiled from Primary Study

Table 2 revealed that ChatGPT was the most preferred AI tool among students. Many respondents also used combinations of Google Gemini, Claude and Perplexity AI. Nearly half of the respondents reported using 2–3 AI tools simultaneously. Daily usage of AI tools was very high among students, indicating strong dependence on AI-assisted learning. Doubt clarification, exam preparation, assignments and research were identified as the major purposes of AI usage.

Objective 2: To identify opportunities and challenges faced while using AI tools.

Table 3: Opportunities and Challenges Faced While Using AI Tools

Statements	SD	D	N	A	SA
Opportunities					
Comparing different AI outputs helps me think more critically about the topic.	35	17	70	35	87
I feel confident in my ability to judge which conflicting AI response is more accurate.	9	19	68	93	55
Conflicting AI answers encourage me to evaluate information more carefully before accepting it.	9	26	52	70	87
Challenges					
Receiving conflicting outputs has reduced my overall trust in AI-generated content.	9	31	74	88	42
Conflicting AI outputs are a sign that AI tools are still unreliable for academic use.	6	40	60	72	66
I feel confused when two AI tools provide	7	23	81	72	61

contradictory information on an academic topic.					

Sources: Compiled from Primary Study

Table 3 indicates that students experience both opportunities and challenges while using multiple AI tools for academic purposes. A considerable proportion of respondents agreed that comparing different AI outputs enhances critical thinking and encourages deeper evaluation of information before accepting it. Respondents also expressed confidence in their ability to judge which AI response is more accurate, indicating the development of analytical and evaluative skills among students.

At the same time, several challenges associated with AI usage were identified. Many respondents reported that conflicting AI outputs reduce their trust in AI-generated content and create confusion during academic decision-making. Respondents also perceived contradictory AI outputs as an indication that AI tools are still unreliable for academic use. Overall, the findings suggest that while conflicting AI explanations promote critical evaluation and independent thinking, they also generate trust-related concerns and cognitive challenges among students.

Table 4: Reliability Statistics for Opportunities and Challenges

Dimension	**Cronbach's Alpha**	**Standardised Alpha**	**No. of Items**
Opportunities	0.712	0.768	3
Challenges	0.705	0.708	3

Sources: Computed from SPSS Output

Reliability analysis was conducted separately for the opportunity and challenge dimensions to assess the internal consistency of the scale items. According to Lee Cronbach, Cronbach's Alpha values above 0.70 indicate acceptable reliability for social science research. Similarly, Jum Nunnally suggested that reliability values above 0.60 are acceptable for exploratory research studies **(Hussey, 2025).**

The Opportunities dimension recorded a Cronbach's Alpha value of 0.712 and a standardised alpha value of 0.768, indicating good internal consistency among the variables related to critical thinking, confidence and careful evaluation of information. Likewise, the Challenges dimension produced a Cronbach's Alpha value of 0.705 and a standardised alpha value of 0.708, indicating acceptable reliability among variables associated with reduced trust, perceived unreliability and confusion arising from conflicting AI outputs. Overall, the reliability results confirm that both dimensions are sufficiently reliable for further factor analysis and interpretation.

Table 5: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.667
Bartlett's Test of Sphericity	Approx. Chi-Square	345.671
	df	15
	Sig.	.000

Sources: Computed from SPSS Output

The Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity were conducted to examine the suitability of the data for factor analysis. According to Henry Kaiser, KMO values above 0.50 are considered acceptable for exploratory factor analysis, while values between 0.60 and 0.70 indicate moderate adequacy. The obtained KMO value of 0.667 indicates satisfactory sampling adequacy for factor analysis. Furthermore, Bartlett's Test of Sphericity was statistically significant (χ^2 = 345.671, p < 0.001), confirming that the variables were sufficiently correlated and suitable for factor extraction.

Factor Analysis

Table 6: Total Variance Explained

Total Variance Explained						
Component	**Initial Eigenvalues**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	2.202	36.70	36.70	2.051	34.17	34.17
2	1.770	29.50	66.20	1.922	32.03	66.20
3	.673	11.22	77.43			
4	.509	8.49	85.92			
5	.456	7.59	93.52			
6	.389	6.48	100.00			
Extraction Method: Principal Component Analysis.						

Sources: Computed from SPSS Output

The factor analysis extracted two components with Eigenvalues greater than 1, satisfying the Kaiser criterion for factor retention. Together, the two extracted factors explained 66.206% of the total variance, which exceeds the minimum acceptable variance level of 60% commonly recommended in social science research. This indicates that the extracted factors adequately explain the major opportunities and challenges experienced by students while using multiple AI tools.

Table 7: Rotated Component Matrix

Rotated Component Matrix[a]		
	Component	
	1	**2**
Comparing different AI outputs helps me think more critically about the topic.	.831	
I feel confident in my ability to judge which conflicting AI response is more accurate.	.805	
Conflicting AI answers encourage me to evaluate information more carefully before accepting it.	.838	
Receiving conflicting outputs has reduced my overall trust in AI-generated content.		.786
Conflicting AI outputs are a sign that AI tools are still unreliable for academic use.		.844
I feel confused when two AI tools provide contradictory information on an academic topic.		.744
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation.		
a. Rotation converged in 3 iterations.		

Sources: Computed from SPSS Output

The rotated component matrix identified two distinct dimensions associated with students' experiences while using multiple AI tools. Variables with factor loadings above 0.70 demonstrated strong associations with their respective components, indicating good construct representation. Overall, the factor analysis confirms that the use of multiple AI tools creates both learning opportunities and significant trust-related challenges among students.

Objective 3: To analyse student responses to conflicting AI-generated outputs.

Table 8: Student Responses to Conflicting AI-Generated Outputs

Statements	SD	D	N	A	SA
I feel confused when two AI tools provide contradictory information on an academic topic. (CONFUSION)	7	23	81	72	61
I try to identify which answer seems more logical before accepting it. (LOGICAL)	4	4	61	95	80
I cross-check conflicting AI responses with textbooks or credible online sources. (CROSSCHECK)	6	25	54	69	90
Receiving conflicting outputs from AI tools has reduced my overall trust in AI-generated content. (TRUST REDUCE)	9	31	74	88	42
I prefer to form my own answer by combining multiple responses. (MULTIPLE RESPONSES)	7	12	48	92	85

Sources: Compiled from Primary Study

Table 8 shows the analysis of student responses toward conflicting AI-generated outputs reveals important insights into how students evaluate and interpret contradictory information provided by different AI tools. A considerable number of respondents agreed or strongly agreed that they feel confused when two AI systems provide contradictory academic information. At the same time, many students reported that they attempt to identify the more logical response before accepting the information, indicating the presence of critical evaluation skills among students.

The analysis further shows that students actively engage in cross-checking AI-generated responses with textbooks and credible online sources to verify accuracy. This suggests that students do not blindly rely on AI-generated information but instead adopt verification strategies when encountering inconsistencies. Moreover, a large proportion of respondents agreed that conflicting outputs from AI tools have reduced their overall trust in AI-generated academic content. This indicates that contradictory AI explanations create uncertainty and trust-related concerns among students.

Another important finding is that many respondents prefer to form their own answers by combining multiple AI responses. This reflects an emerging trend of integrative learning behaviour where students compare, evaluate and synthesise information from different AI platforms rather than depending solely on a single AI-generated response. Overall, the findings suggest that conflicting AI-generated outputs simultaneously promote critical thinking and verification practices while also contributing to confusion and reduced trust in AI-generated content.

Table 9: Correlation Analysis of Student Responses toward Conflicting AI-generated Outputs

		Confusion	Logical	Cross check	Trust Reduce	Multiple Responses
Confusion	Pearson Correlation	1	.559**	.299**	.512**	.193**
	Sig.		.000	.000	.000	.002
Logical	Pearson Correlation	.559**	1	.587**	.452**	.341**
	Sig.	.000		.000	.000	.000
Cross check	Pearson Correlation	.299**	.587**	1	.354**	.355**
	Sig.	.000	.000		.000	.000
Trust Reduce	Pearson Correlation	.512**	.452**	.354**	1	.246**
	Sig.	.000	.000	.000		.000
Multiple Responses	Pearson Correlation	.193**	.341**	.355**	.246**	1
	Sig.	.002	.000	.000	.000	

***. Correlation is significant at the 0.01 level (2-tailed).*

Sources: Computed from SPSS Output

Pearson correlation analysis was conducted to examine the relationships among students' responses toward conflicting AI-generated outputs. The findings indicate that all variables are positively and significantly correlated at the 0.01 level, suggesting meaningful associations among confusion, logical evaluation, cross-checking behaviour, trust reduction and the tendency to combine multiple AI responses.

The analysis reveals a moderate positive correlation between confusion and logical evaluation ($r = 0.559$, $p < 0.01$), indicating that students who experience confusion due to contradictory AI outputs tend to engage more actively in evaluating the logical accuracy of responses. Similarly, confusion is positively associated with reduction in trust toward AI-generated content ($r = 0.512$, $p < 0.01$), suggesting that conflicting AI explanations significantly influence students' trust perceptions.

A strong positive relationship was observed between logical evaluation and cross-checking behaviour ($r = 0.587$, $p < 0.01$), implying that students who critically assess AI responses are more likely to verify information through textbooks or credible online sources. Furthermore, students who combine multiple AI responses also tend to engage in logical evaluation and cross-checking practices. Overall, the results indicate that conflicting AI outputs encourage analytical thinking and verification behaviour among students while simultaneously creating confusion and reducing trust in AI-generated academic content.

VII. FINDINGS AND DISCUSSION

The findings of the study indicate that generative AI has become deeply integrated into students' academic activities. The increasing dependence on multiple AI tools reflects the growing acceptance of AI-assisted learning systems in higher education. However, the study also highlights the complexity of trust formation when students encounter contradictory AI-generated explanations.

The results support previous studies that identified trust and reliability as major determinants of AI adoption. Students were found to engage actively in logical evaluation and verification when conflicting outputs occur. This suggests that contradictory AI explanations may promote critical thinking rather than passive learning behaviour.

At the same time, the study reveals significant challenges associated with conflicting AI outputs. Students reported confusion, uncertainty and reduced trust toward AI-generated academic content. Such findings align with earlier studies emphasising the risks of AI hallucinations and inconsistent information.

An important contribution of the study is the identification of integrative learning behaviour among students. Rather than depending on a single AI response, many students compare and combine outputs from multiple AI systems before forming conclusions. This reflects the emergence of a more analytical and verification-oriented approach toward AI-assisted learning.

The study, therefore suggests that AI tools should not be treated as absolute sources of truth. Educational institutions must encourage students to develop digital literacy, critical thinking and verification skills to ensure responsible use of generative AI technologies.

VIII. CONCLUSION

AI has become an important educational support system for students. The study found that students widely use AI tools for doubt clarification, assignments, exam preparation and research activities. While AI systems improve accessibility and learning efficiency, conflicting AI-generated outputs create confusion and trust-related challenges among students. The findings reveal that students do not blindly accept AI-generated content. Instead, many students evaluate logical consistency, compare multiple responses and verify information using textbooks or credible sources. This indicates the growing importance of critical thinking in AI-assisted education. However, contradictory AI explanations also reduce trust in AI-generated academic content and create uncertainty during decision-making. Therefore, students must be encouraged to use AI responsibly and critically rather than relying entirely on automated systems. The study concludes that generative AI tools are highly beneficial for education, but effective learning requires human judgment, analytical thinking and proper verification practices. Educational institutions should promote AI literacy programs and ethical guidelines to ensure safe, transparent and responsible use of AI technologies in academic environments.

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