Comparative Impact of AI and Search Technologies on Outcome-Based Learning in Engineering Education

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***Abstract*—AI and advanced search technologies are transforming engineering education by enhancing student outcomes, entrepreneurship, and employability through the development of tech-driven skills. This study employs outcome-based experimental learning to analyze the comparative impact ofGenerative AI (e.g., ChatGPT), non-generative AI tools, and traditional search engines (e.g., Google Search) on engineering education. Ninety students participated in a controlled experiment, solving a technical problem using these three methods. The study evaluated solution efficiency and learning outcomes based on a range of assessment criteria. Results revealedthat Generative AI facilitated faster problem-solving but often ledto weaker conceptual understanding, while non-generative AItools provided more accurate solutions, albeit with slower response times. Google Search was effective for information retrieval but posed challenges in synthesizing coherent and integrated solutions. These findings underscore the importance ofadopting a balanced approach that combines the strengths of AI tools with rigorous assessment methods to promote deep learning and critical thinking. The study highlights the relevance of evaluating evolving technologies in education and calls for curriculum and assessment strategies that adapt to these advancements. Future research should explore the long-term impact of AI on knowledge retention and its application across diverse engineering domains.**

***Keywords*— Engineering Education, Generative AI, Search Technologies, Outcome Based Education.**

ICTIEE* Track*: Technology Enhanced Learning
ICTIEE Sub-Track: Engineering Education, Generative AI, Search Technologies, Outcome-Based Education

I. INTRODUCTION

ENGINEERING education aims to equip students with essential skills such as problem-solving, critical thinking, and innovation to address real-world challenges. With the advent of advanced technologies, tools like generative AI, non-generative AI, and search engines have significantly impacted the learning processes in engineering education. These tools offer opportunities for personalized learning, efficient information retrieval, and innovative

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teaching methodologies, making them increasingly relevant in outcome-based education (OBE). OBE, a structured and goal-oriented teaching approach, has been shown to improve student learning, subject delivery, and instructional techniques (Zamir et al., 2022).

Generative AI tools such as ChatGPT, Bard, and Perplexity hold potential to revolutionize engineering education by providing real-time content, streamlining accreditation efforts, and optimizing faculty workloads (Santos et al., 2024). However, as Qadir (2023) highlights, these tools also face limitations, including biases, misinformation, and ethical concerns, necessitating the adaptation of educational strategies to maximize their benefits while mitigating challenges.

Search-as-learning research explores enhancing traditional search engines with advanced layers to deliver more context-appropriate content for learning scenarios (Homte et al., 2022). While these tools facilitate information gathering, their effectiveness in synthesizing and applying knowledge remains a challenge. Borrego et al. (2015) emphasize the need for systematic review methodologies in education research, focusing on quality measures such as education level, sources, and evaluative criteria.

This study seeks to evaluate the comparative effectiveness of generative AI, non-generative AI, and search engines in fostering outcome-based learning in engineering education. By analyzing their impact on problem-solving, critical thinking, and innovation, the research aims to provide actionable insights for curriculum design, teaching practices, and assessment strategies in the evolving landscape of engineering education.

Research Questions

The research addresses the following questions:

1. How do generative AI tools such as ChatGPT, non-generative AI tools, and traditional search engines like Google influence learning outcomes in engineering education?
2. To what extent does the efficiency and accuracy of problem-solving vary among students using generative AI, non-generative AI, and traditional search tools, particularly under time constraints?
3. How do different evaluation methods (subjective vs. objective assessments) impact students' performance and conceptual understanding when using these tools?

II. II. LITERATURE REVIEW

AI is revolutionizing education by enhancing learning outcomes, personalized education, and teaching efficiency, according to numerous studies.

A. AI and Learning Outcomes:

Wu and Yu (2024), Ma et al. (2014), and Huang et al. (2023) have all emphasized the transformative impact of AI technologies on learning outcomes. Ma et al.'s meta-analysis underscored the effectiveness of intelligent tutoring systems, AI chatbots, and personalized video recommendations in improving educational experiences. Similarly, Huang et al. (2023) highlighted the potential of AI in t h e flipped classroom settings, demonstrating its ability to enhance student engagement and motivation. These studies collectively suggest

TABLE I
PHASE 1: COMPARATIVE

Feature	Generative AI	Other AI Tools	Google Search
Efficiency	- Fast response time for problem-solving.	- Slower due to systematic and step-by-step processing.	- It is time-consuming to sort through large volumes of information.
Conceptual Understanding	- This may lead to weaker conceptual foundations due to a focus on efficiency.	- Strengthens understanding by providing structured, detailed explanations.	- Lacks guidance and explanation, leaving users to piece concepts together independently.
Accuracy	- Prone to hallucinations or fabricated information.	- Highly accurate in specific domains due to reliance on structured datasets.	- Credibility depends on the user's ability to identify reliable sources.
Creativity	- Generates novel ideas and solutions, making it highly versatile.	- Limited to predefined algorithms and lacks innovation or creative output.	- Allows exploration of diverse ideas but does not generate new content.
Personalization	- Adapts to user input, offering an interactive and tailored learning experience.	- Less interactive and not designed for dynamic personalization.	- No personalization; users must manually refine searches.
Scope	- Broad scope across various topics but less domain-specific depth.	- Narrower scope, but excels in domain-specific tasks.	- Extremely broad and interdisciplinary, but often lacks focus on a specific problem.
Independent Learning	- Risk of over-dependence, reducing students' ability to think critically or work independently.	- Encourages guided problem-solving but does not foster autonomy.	- Promotes independent evaluation, synthesis, and decision-making skills.
Accessibility	- Requires internet access and may involve costs depending on the tool.	- Accessibility depends on the tool; often specialized software or subscriptions are required.	- Free and widely available to all users with internet access.
Information Overload	- Provides concise outputs, minimizing cognitive overload.	- Structured output ensures focused and relevant information.	- Can overwhelm users with excessive or irrelevant search results.
Application in OBE	- Effective for generating ideas and boosting engagement but may fall short in measuring deeper learning outcomes like problem-solving processes.	- Strong for reinforcing concepts and providing actionable insights, aligning well with Outcome-Based Education goals.	- Useful for exploring OBE concepts but lacks structured content to directly map learning outcomes.

that AI tools, when appropriately integrated, can significantly enrich teaching methodologies and learning environments.

B. AI in Educational Administration and Instruction

AI is revolutionizing educational administration and instructional practices, improving teaching quality, and providing personalized learning materials. This enhances student retention and efficiency. Chen et al. (2020) and Zhai et al. (2021) highlight how AI bridges the gap between pedagogical techniques and the learning process, making education more efficient and effective.

C. AI and Technological Literacy

Stolpe and Hallström (2024) emphasize that AI education aims to deepen students' understanding of technology, preparing them for future advancements. They emphasize the critical role of humans in AI, fostering a comprehensive understanding of its implications.

D. AI's Impact on Cognitive Presence and Learning Environment

Wang's study on AI's role in educational settings found that learners' perceptions of AI's humanized appearance positively impact learning outcomes. However, a strong teaching presence can negatively affect learning outcomes, suggesting a delicate balance between AI and human interaction.

E. Generative AI in Higher Education

According to Ivanov et al. (2024), Generative AI tools are revolutionizing higher education by improving attitudes, subjective norms, and behavioral control. This has implications for management and policy in educational settings. AI's integration into education enhances learning outcomes, administration, instruction, and technological literacy. The evolving role of AI in education presents new opportunities and challenges, necessitating ongoing research and exploration.

The quality of education is being significantly enhanced by the use of various AI tools as depicted in Figure No. 1. Generative AI tools offer enhanced learning efficiency, while intelligent tutoring systems provide personalized feedback. AI in educational administration automates tasks, improving teaching quality and reducing administrative burdens. AI education deepens students' understanding of technological concepts, preparing them for future advancements. However, the design and presentation of AI can influence learning outcomes, necessitating a balance between AI and human interaction. Generative AI in higher education can improve attitudes and behavioral control but requires a balanced approach to optimize learning outcomes.

III. RESEARCH GAP

Existing studies on AI's effectiveness in problem-solving and Outcome-Based Education (OBE) are limited. The gap lies in understanding the differences between Generative AI, non-generative AI, and Google Search. The research also lacks research on how assessment methods, such as objective, subjective, and oral exams, influence student performance after exposure to AI tools. This research is crucial for understanding the impact of AI on problem-solving efficiency in engineering education.

IV. STATEMENT OF THE PROBLEM

Due to the increased usage of Internet resources Generative AI and search technologies have a widespread impact on student learning. This study explores the impact of AI and search technologies on student learning in engineering education, focusing on problem-solving efficiency, conceptual understanding, and overall learning outcomes.

V. NEED OF THE STUDY

Outcome-based education (OBE) in Indian engineering education, adopted through the Washington Accord, has shown a promising impact, but further training is needed for effective curriculum design, delivery, assessment, evaluation, and reflection (Jadhav et al(2020). OBE (Outcome Based Education) focuses on the learning outcome and the level of ability to perform the outcome expected of students after using teaching-learning pedagogies. Syeed et al (2022) highlighted that OBE is a key strategy in engineering education, enabling students to solve real-life engineering problems and master various skill sets, thereby enhancing their academic equivalency and accreditation. This study aims to optimize learning outcomes in engineering education by integrating AI and search technologies effectively, focusing on understanding the effectiveness of Internet and AI-based resources.

VI. OBJECTIVES OF THE STUDY

1. To assess the impact of different AI and search technologies on students' ability to solve engineering problems efficiently.
2. To evaluate the effectiveness of Generative AI, Other AI, and Google Search in enhancing learning outcomes within an outcome-based education framework.
3. To compare the effect of different evaluation methods (objective, subjective, and oral exams) on student performance and conceptual understanding after using these technologies.

VII. HYPOTHESIS

H_1: Students using Generative AI (Group A) will demonstrate faster solution times but potentially weaker conceptual understanding than other groups.
H_2: Students using other AI tools (Group B) will provide more accurate solutions, but their problem-solving process will take longer due to domain-specific precision.

H_3: Students using Google Search (Group C) will gather extensive information but will struggle with synthesizing it into an efficient and coherent solution within the time limit.

VIII. METHODOLOGY

1) *Introduction*

The study compares the effectiveness of three AI tools - ChatGPT, Other AI tools, and Google Search - in enhancing engineering education. The research uses an experimental design to assess efficiency, conceptual understanding, and problem-solving ability. Undergraduate engineering students were divided into three groups: Group A, Group B, and Group C.

The experimental setup included a pre-test to assess baseline knowledge, a test phase where students were tasked with solving engineering problems using their assigned tools, and a post-test to measure retention and understanding. The study used ANOVA tests to identify significant differences in solution times and assessment scores, as well as Pearson correlation tests to analyze the relationship between accuracy and time. The study's limitations include a small, single-institution sample size, and future studies should include more diverse populations for broader applicability.

2) *Study Design*

This study involves three groups of engineering students, each assigned a similar technical problem. Each group is asked to solve the problem using different tools:

Target Population: Engineering students enrolled in the undergraduate or postgraduate programs at KE Society's Rajarambapu Institute of Technology, Islampur.

Sample Size: 90 students.

Sample Selection: Purposive Random sampling method

Group Formation:

The study involves three phases: Initial Experiment, Reorganization and Reassessment, and Data Analysis and Hypothesis Testing. The methodology is designed to assess the comparative effectiveness of Generative AI (ChatGPT), other AI tools, and traditional Google search in an outcome-based learning environment. Students are randomly assigned to three groups, and their performance is monitored. The data is then analyzed using MS Excel and R Studio, and conclusions are drawn. Ethical considerations include informed consent, data privacy, and data validation.

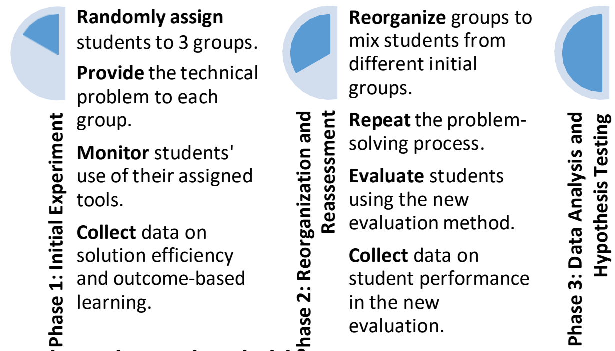

Fig. 1. Phases of Research Methodology

Total Groups: Three groups, each consisting of 30 students.

Group A: Uses ChatGPT (Generative AI) for assistance.

Group B: Uses other AI tools, such as IBM Watson or Wolfram Alpha.

Group C: Relies solely on traditional Google search.

The experimental problem is designed to test students' understanding of engineering concepts, problem-solving skills, and application of knowledge in a practical setting.

3) *Time Constraints*

Students are given a 2-hour time limit to work in the lab. During this period, they are expected to:

Research the problem using their assigned tool.

Develop a solution or approach to solving the problem.

Present their solution in written form.

4) *Data Collection*

Solution Efficiency: Measured by assessing the quality, correctness, and completion of the solution within the given time.

Outcome-Based Learning: Tracked through formative and summative assessments based on outcome-based education principles.

5) *Tools Used in the Study*

The Researcher used tools for Data Analysis and Hypothesis Testing

- MS Excel
- R Studio 2024.04.2 Build 764
- R framework 4.4.1

Students Teams Used

- ChatGPT Generative AI
- Any Other AI Tool of their Choice
- Google Search Browser

6) Reorganization and Reassessment

After the experiment's first phase, the teams are reorganized, mixing students from the three groups to form new teams. The problem-solving process is repeated, but this time, the evaluation method is changed. Students are assessed either through:

1. Objective Exam: A multiple-choice test focusing on conceptual understanding.
2. Subjective Exam: A written essay analyzing technical problems.
3. Oral Exam: An oral defense of their solution before a panel of evaluators.

7) Assessment Criteria

-Objective Measures: Focus on the accuracy of answers, time efficiency, and comprehension.

Subjective Measures: Evaluate the depth of understanding, quality of reasoning, and problem-solving approach.

Oral Defense: Assesses communication skills, clarity of thought, and the ability to justify the solution.

Results

8) Group Comparison

Group A (ChatGPT): Demonstrated quicker response times and more detailed solutions. However, dependency on generative AI led to a weaker understanding of core concepts.

Group B (Other AI Tools): Produced more accurate and context-specific solutions but took longer to formulate answers.

Group C (Google Search): Students performed well on information gathering but struggled with synthesizing a coherent and efficient solution in the limited time.

TABLE I
PHASE 1: PROBLEM-SOLVING EFFICIENCY

Group	AVERAGE CORRECTNESS (OUT OF 100)	AVERAGE COMPLETENESS (OUT OF 100)	AVERAGE TIME TAKEN (OUT OF 120 MINUTES)	overall solution efficiency (weighted out of 100)
A (Generative AI)	80	75	90 minutes	85
B (Other AI)	95	85	110 minutes	87
C (Google Search)	70	60	115 minutes	72

The study analyzed the performance of three groups of engineering students using various AI tools: ChatGPT, other AI tools, and Google Search. The results from table no. I showed that Group B had the highest average correctness,suggesting that the "Other AI" tools were particularly effectivein solving the problem. Group A had similar levels of correctness, slightly outperforming Group C. Group B also excelled in completeness, indicating their solutions were more comprehensive. Group A was the most efficient in terms of time taken, while Group C struggled to find relevant information. Overall, Group B consistently outperformed the other groups in terms of solution efficiency. The study suggests that further analysis could reveal variations in performance, problem complexity, student familiarity with AI tools, and qualitative feedback from students. This could provide insights into their experiences using different tools and their perceptions of their performance.

9) Efficiency of Solutions

Generative AI tools, such as ChatGPT, demonstrated efficiency in generating comprehensive solutions quickly, though some responses exhibited a trade-off between speed and depth.

Other AI tools provided responses with higher domain-specific accuracy but required more time for processing.

Traditional search engines, like Google Search, offered extensive raw information, necessitating additional effort from students to filter, comprehend, and synthesize the data into applicable solutions.

IX. EVALUATION OUTCOMES

Objective Exam: Students from Group B performed better due to the precise nature of AI tools that focus on specific fields of knowledge.

Subjective Exam: Group A excelled in providing broad, creative solutions, but struggled with in-depth technical justifications.

Oral Exam: Group C students showed better adaptability in explaining their thought process, despite less efficient solutions.

TABLE II
PHASE 2: ASSESSMENT SCORES (POST REORGANIZATION)

Group	Objective Exam (out of 100)	Subjective Exam (out of 100)	Oral Exam (out of 100)	Average Assessment Score (ou 100)
A (Generative AI)	75	65	80	73.33
B (Other AI)	85	80	75	80
C (Google Search)	70	75	85	76.67

Table no. II shows an analysis of the performance of three groups (A, B, and C) on three assessments: Objective Exam, Subjective Exam, and Oral Exam. Group B outperformed Group A and Group C, with Group B's strongest performance in the Objective Exam. The average scores for all three groups were relatively high, indicating good performance. Group B demonstrated higher conceptual understanding and knowledge retention in the Objective Exam, while Group A's strongest performance was in the Oral Exam. Possible explanations include the reorganization effect, tool effectiveness, and individual differences among students. Further analysis could include individual student scores, qualitative data, and longitudinal studies. In conclusion, Group B outperformed Group A and Group C in all three assessments, but both Group A and Group C demonstrated strong overall performance. Further research is needed to determine the optimal combination of tools and assessment methods for engineering

Students.

X. HYPOTHESIS TESTING

The study aimed to determine the difference in solution times, assessment scores, and the relationship between accuracy and time among three groups (A, B, and C). Statistical tests were conducted, including ANOVA for solution times and assessment scores, and Pearson Correlation for accuracy and time. The results showed significant differences in solution times and assessment scores among the groups, with Group B having faster solution times than Group A and Group C. However, no significant correlation was found between accuracy and time. The null hypothesis was rejected.

XI. RESULTS DISCUSSION AND FINDINGS

The study reveals a clear difference in how various tools influence learning outcomes in engineering education. Generative AI, while efficient, may promote superficial learning if not supplemented with deeper analytical skills. Other AI tools, which are more domain-specific, encourage precision but at the cost of speed. Traditional search engines like Google pose challenges in synthesis and time management, though those are powerful in information retrieval. Outcome-based education focused on real-world problem-solving, benefits from integrating AI tools but requires careful assessment methods to ensure that students are not only solving problems but also comprehending the underlying principles.

XII. RUBRICS FOR EVALUATION

Rubrics offer a structured framework for evaluating the performance of various tools and methodologies.

TABLE III
RUBRICS USED FOR EVALUATION

Criteria	Weight (%)	Focus	Evaluation Method	Goal
Solution Times	30%	Efficiency in task completion	Time logs from lab sessions	Promote quick and effective use of tools
Assessment Scores	40%	Quality and correctness	Predefined grading criteria	Measure problem-solving and clarity
Problem Understanding	20%	Comprehension of tasks	Formative tests and observatio n n	Assess the depth of understanding
Team Collaboration	10%	Group Contribution and teamwork	Peer and Facilitator feedback	Encourage Collaboration and communication

They assess solution times, assessment scores, and problem-solving understanding. The rubric consists of four criteria: solution times, assessment scores, problem understanding, collaboration and teamwork, and ethical use of tools. The performance levels range from excellent to poor, indicating the accuracy and correctness of problem-solving and solutions provided. The rubric also evaluates the ability to work effectively in a team, demonstrating the importance of understanding and adhering to ethical guidelines. Overall, the rubric provides actionable insights for improvement.

Rubrics are a systematic framework for evaluating tools based on specific performance criteria. They provide a clear, objective, and standardized approach to assess and compare tools based on specific performance criteria. The components of rubrics are shown in Table No. III includes solution times, assessment scores, problem understanding, collaboration and teamwork, and ethical use of tools. The significance of these components lies in their ability to measure efficiency, accuracy, understanding, and adherence to ethical guidelines. Excessive time can indicate inefficiency, while good results align with expected benchmarks. Understanding the significance of these components is crucial for identifying the most effective tools for users. By assigning scores and feedback, rubrics help make informed decisions for tool adoption and improvement.

The study in table no. IV found significant differences in solution times, assessment scores, and Pearson correlation betweendifferent groups. Group A (Generative AI) had moderate solution times and high accuracy, while Group B (Other AI) had the best overall performance in solution times and assessment scores. Group C (Google Search) had the lowest efficiency in solution times but high accuracy in assessments. Group B consistently outperformed other groups in efficiency and assessment scores, making it the most effective tool in the given evaluation. No significant correlation was observed between accuracy and time across all groups.

TABLE IV
PHASE 2: ASSESSMENT SCORES (POST REORGANIZATION)

Test	hypothesis test result	significance	decision
Solution times	Anova p-value = 3.94e-06	Significant	Reject H_0; significant differences exist between groups
Post-hoc test for solution times	Group b vs. Group A: p = 0.0000153 < 0.05	Significant	Significant differences between group A and the others; marginal difference between group B and C
	Group c vs. Group a: p = 0.0000039 < 0.05		
	Group c vs. Group B: p = 0.0263 < 0.05		
Assessment scores	Anova p-value = 0.00903	Significant	Reject H_0; significant differences exist between groups
Post-hoc test for assessment scores	Group b vs. Group A: p = 0.00734 < 0.05	Significant for Group B vs. Group A; not significant for others	Significant difference between group B and group A; no significant differences between other pairs
	Group C vs. Group A: p = 0.1235 > 0.05		
	Group C vs. Group B: p = 0.1122 > 0.05		
Pearson correlation (accuracy & time)	P-value = 0.9362	Not significant	Fail to reject H_0; no significant correlation
A (generative ai)	75	65	80
B (other ai)	85	80	75
C (google search)	70	75	85

XIII. SUGGESTIONS

To effectively integrate AI into education, a balanced approach is needed as portrayed in table no. V. This includes hybrid learning, focusing on AI as a tool rather than a replacement for human instruction. Curriculum design should prioritize conceptual understanding, problem-solving skills, and ethical considerations. Effective assessment strategies should use diverse methods, and teacher training should focus on AI literacy and pedagogical skills. Continuous evaluation andimprovement are essential to monitor the impact of AI toolson student learning outcomes. Hybrid learning comprises mainly combining AI with traditional human instruction tocreate a personalized learning experience. AI is used for automated tasks like grading and feedback, allowing teachers to focus on more complex activities.

TABLE V
SUGGESTIONS

Suggestion Category	Key Points
Hybrid Learning	AI with human instruction - a personalized experience.
AI as a Tool	AI as a supplementary resource, not a replacement.
Curriculum Design	Conceptual understanding, Problem-solving, and Ethical considerations.
Assessment Strategies	Diverse methods and AI-powered assessment tools.
Teacher Training	Teachers with AI literacy and pedagogical skills.
Continuous Evaluation	Monitor and improve AI integration based on data.

AI is emphasized as a supplementary tool, not a complete replacement for human educators. Curriculum design prioritizes conceptual understanding, critical thinking, and problem-solving skills, and integrates AI-related concepts throughout the curriculum. Assessment strategies use various methods andAI-powered tools to evaluate students ‘understanding levels and skills. Teacher training equips teachers with AI literacy and pedagogical skills, and a culture of experimentation and continuous learning encourages the adoption of innovative AI-based approaches. Continuous evaluation and improvement are necessary to refine AI integration strategies and optimize the learning experience.

CONCLUSION

The study highlights the need for a balanced approach to outcome-based engineering education, incorporating AI tools as supportive aids and rigorous assessment strategies to cultivate critical thinking, creativity, and deep conceptual understanding. Generative AI has shown efficiency in generating solutions, but it may come at the cost of depth and conceptual rigor. Non-generative AI tools provide domain-specific accuracy but often require more time for problem-solving. Traditional search engines like Google excel in gathering information but pose challenges in synthesizing scattered data into coherent solutions. The study also emphasizes the need for future research to explore the scalability, retention, and adaptability of AI-driven learning across disciplines and skill levels. To remain relevant, educational research must periodically re-evaluate the efficacy of tools and methods, ensuring teaching practices evolve alongside technological advancements. This adaptive approach will maximize the potential of AI and search tools while maintaining focus on foundational learning goals.

FUTURE WORK

This research explores the potential of AI in engineering education, focusing on its long-term impact on knowledge retention and the development of critical thinking skills. It also addresses ethical considerations such as bias and misinformation in AI-generated content and the ethical implications of increasing reliance on AI in education. The findings can be applied to various engineering disciplines and institutional factors, such as curriculum design and faculty training. AI can be used to create personalized learning paths and adaptive assessments, providing real-time feedback and adjusting difficulty levels based on student performance. Interdisciplinary collaboration between engineering and humanities/social sciences is encouraged to address the ethical and societal implications of AI in education. The research also encourages interdisciplinary research to explore the broader impact of AI on education, including cognitive science, psychology, and educational technology.

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APPENDIX

Abbreviations

AI	Artificial Intelligence
OBE	Outcome Based Education