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A Comparative Analysis of Generative AI Models for Improving Learning Process in Higher Education

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***Abstract*-This study comprehensively analyses ten advanced generative AI models including GPT-4, Microsoft Copilot, Claude, DeepSeek, Pi and others to assess their applicability in higher education for computer science students. The study uses a mixed-method approach involving qualitative and quantitative analyses to evaluate these models across four key groups: architecture, content quality, adaptability, and performance. The results show that while each model has certain strengths - such as GPT-4's content creation capabilities and Pi's adaptability - none is the optimal choice across all clusters. The study emphasizes the importance ofaligning the choice of AI tool with specific educational goalsand needs. It also emphasizes the need for continuous evaluation of AI technologies to ensure their effectiveness in dynamic educational environments. The study contributes to the growing discourse on AI in education by offering a sound framework for evaluating AI models and guiding their implementation in educational environments.**

Keywords— **generative AI, higher education, computer science,educational technologies, Evaluation of AI models**

I. Introduction

This template, Inventors have long dreamed of creating a thinking machine. The first time humans thought about programmable computing machines, they wondered if they could become intelligent - a hundred-plus years before the computer was built. Today, artificial intelligence (AI) is a burgeoning discipline with numerous applications. We want intelligent programs that can automate routine tasks, understand speech and images, make medical diagnoses and support scientific research [1].

With the development of Artificial Intelligence (AI) and its abilities, generative AI models are becoming an important tool in the educational process. These models are capable of creating texts, writing code, analyzing data and supporting interactive sessions, making them indispensable aids in student learning. Generative AI models are used in a variety of educational contexts, including creating adaptive learning materials, automating code validation, conducting virtual labs, and analyzing data.

Each year, more and more research shows that the use of AI can significantly improve the educational process, increase student achievement, and ease the burden on instructors. For example, models such as GPT-4 demonstrate high accuracy in text and code generation, allowing them to create high-quality learning materials and check student work with a high degree of automation. In addition, such models can analyze large amounts of data, which is useful for instructors when developing individual learning plans and assessing student progress.

Which AI tool is better than ChatGPT? Determining which AI tool is better than ChatGPT depends on specific requirements and use cases. While ChatGPT is a highly effective tool for creating text responses and participating in dialogue interactions, other well-known AI tools offer similar features. Is there another AI similar to ChatGPT? Some popular alternatives include OpenAI's GPT-3, Boom Hugging Face, Microsoft Bing Chat, and Google Bard. Each tool has its own strengths and weaknesses, so it's important to evaluate them against your specific needs to determine which one is better suited to your requirements.

This paper conducts a comparative analysis of ten advanced AI-driven content creation models (GPT-4, Llama 3.1 405B, Microsoft Copilot, Gemini, Claude, DeepSeek, Pi, YaGPT3, GigaChat, Mistal Le Chat) in terms of their application in higher education for computerscience students.

The main objective of this research is to identify the most effective and applicable generative AI models for supporting students and automating routine tasks of instructors. This research aims to explore how AI models can be used for personalized feedback and support in the learning process without replacing critical aspects of learning, such as the development of independent thinking skills. Given that many universities have measures in place to restrict the use of AI in order to maintain academic standards, this study focuses on how AI can complement traditional pedagogical approaches and enhance their effectiveness. Considering the different aspects and characteristics of these models will help educational institutions to choose the most appropriate tools to implement in the learning process.

II. Literature review

In order to improve the learning process in higher education institutions, especially for computer science students, a comparative analysis of second generation models reveals important strategies and methodologies aimed at optimizing educational outcomes. In reference [10] notes that the use of blended learning methods significantly improves the effectiveness of practice-oriented learning in universities, emphasizing the importance of creating pedagogical conditions that meet modern educational standards. In turn, the study in reference [11] presents a blended learning model that successfully integrates different educational activities, which provides optimal outcomes in both face-to-face and distance

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learning, allowing the diverse needs of students studying in different educational environments to be met.

Additionally, the study in reference [12] focuses on the development of a model of graduate satisfaction in higher education institutions, highlighting the importance of considering students' views in order to effectively allocate resources and create educational programs that meet their needs. This focus on student satisfaction and feedback is key in the context of improving the educational process for computer science students, as it enables the tailoring of educational programs to meet students' expectations and enhance their overall educational experience.

In addition to student satisfaction, the study in reference [13] emphasizes the importance of digital technologies and innovative teaching methods in the educational environment. Their work examines models of digital transformation that focus on designing information objects, interacting with other institutions, and using distance learning platforms. These models aim to foster innovation and improve the efficiency of the educational process, which is particularly important in the context of computer science education.

Furthermore, a study in reference [14] emphasizes the benefits of using learning analytics in universities, including improved student learning outcomes, curriculum design and teaching effectiveness. This data-driven approach is consistent with the current trend of using predictive analytics, as discussed in references [9, 15], to optimize student performance and tailor educational interventions to meet individual learning needs.

Overall, a comparative analysis of second-generation models for improving learning in higher education, especially for computer science students, highlights the importance of blended learning, student satisfaction, digital transformation, learning analytics and personalized learning approaches. All these elements play a key role in improving the quality and efficiency of the educational process.

Generative AI models can also significantly improve student performance and the quality of student learning, especially in technical disciplines [16, 17]. In references [5, 18, 19] show that such models can automatically generate learning materials, check code and conduct virtual labs, which significantly reduces the workload of teachers, allowing them to focus on more complex aspects of learning. In addition, they note that generative models such as GPT-4 can accelerate the learning process of programming and reduce the time it takes to check students' work.

The study in reference [20] focuses on using generative AI models to create adaptive learning materials, and shows that such models can create personalized learning plans, which has a positive impact on student performance. In turn, in reference [3] analyzed the use of AI to automate code checking and program writing, showing that advanced models can significantly accelerate programming learning.

In reference [21] investigated the integration of generative AI models into educational platforms and learning management systems. Their results showed that such integrations promote a more interactive and personalized learning environment, which is particularly important for increasing student engagement. In reference [22] studied the impact of generative AI models on student engagement and found that using AI to create interactive learning materials increased both student engagement and performance.

Meanwhile, in reference [23] focused on the ethical aspects of using generative AI models in education, emphasizing the need for transparency and responsibility when using such technologies. In reference [4] investigated the use of AI for data analysis and visualization, showing that AI can help students better understand complex concepts and data. In reference [7] investigated the use of AI to create virtual labs and simulations, improving students' understanding and preparation for practical tasks. In reference [24] explored the use of AI to automate administrative tasks in educational settings, which can reduce time spent on routine tasks and improve teacher effectiveness.

In reference [25] investigated the use of generative AI models to create interactive tutorials and found that such tutorials can improve students' interaction with learning materials and increase their interest in learning. In reference [8] investigated the impact of generative AI models on academic integrity, emphasizing the need to develop methods to prevent plagiarism and ensure transparency when using AI for educational purposes.

In addition, FlexOS conducted a comprehensive study of the effectiveness and potential applications of AI tools in various domains, including education. The study evaluated the current level of development of AI tools such as GitHub Copilot and Hugging Face and their impact on learning to code and application development [2].

The integration of generative AI models and modern teaching methods into the educational process opens new opportunities to improve the quality and efficiency of learning, which is especially relevant for computer science students.

III. Methodology

The main objective of this research is to conduct a comprehensive assessment of ten cutting-edge generative AI models—GPT-4, Llama 3.1 405B, Microsoft Copilot, Gemini, Claude, DeepSeek, Pi, YaGPT3, GigaChat, and Mistal Le Chat—focusing on their suitability for educational settings. The study examines how these models can be integrated into higher education, particularly in computer science programs, to enhance the student learning experience. It emphasizes understanding the interplay between architecture, content quality, adaptability, and performance, with a central focus on educational applicability.

This mixed-methods research design combines quantitative and qualitative analyses, organized into four key steps: model selection, evaluation criteria definition, data collection, and analysis. The AI models were chosen based on their relevance, documented performance, and potential for educational use, ranging from established models like GPT-4 to emerging ones like Mistal Le Chat. A thorough literature review informed this selection, ensuring a broad evaluation of models with unique strengths and limitations.

The study evaluates the models based on four key clusters:

Architecture: Examines the model's computational frameworks, scalability, and algorithms, essential for handling complex educational tasks.

Content Quality: Assesses accuracy, relevance, and pedagogical value, crucial for generating content that meets educational standards.

Adaptability: Focuses on the model's flexibility to adjust to different learning environments and curricular needs, critical for tailoring content to individual learners.

Performance: Evaluates efficiency, response time, and resource utilization, key for practical deployment in real-time educational settings.

These criteria are assessed using a mix of quantitative metrics (processing speed, accuracy rates) and qualitative assessments (content coherence and relevance).

Data collection for this study employed a multi-faceted approach, combining direct interactions with the AI models and a thorough review of existing literature. Each model was subjected to standardized tasks simulating real-world educational scenarios, such as generating explanations of complex concepts, creating lesson plans, and engaging in adaptive learning dialogues. This allowed for practical evaluation of the models' capabilities in education.

For qualitative assessment, thematic analysis was used to categorize and interpret the content generated by the models. This method helped identify recurring themes and patterns, offering insights into each model's strengths and weaknesses. The analysis followed established frameworks for evaluating educational technologies, ensuring best practice alignment[28, 29, 30].

Quantitative data were analyzed using statistical methods to assess performance metrics like response time, accuracy, and resource utilization. These metrics were compared across models to highlight which excelled in specific areas and identify limitations that could affect their educational applicability.

Fig.1 illustrates the categorization of AI models into four key clusters—Architecture, Content Quality, Adaptability, and Performance & Efficiency—with a central emphasis on Educational Applicability. The visual representation aids in understanding how the models were grouped and analyzed according to their relevance and potential impact in educational contexts.

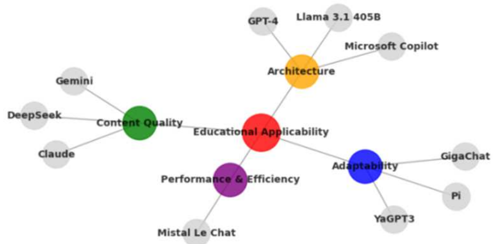

Figure 1. Categorization of AI Models in the Context of Educational Applicability

Fig.2 illustrates the interconnectedness of the evaluation criteria and highlights the importance of each cluster in assessing the educational potential of the AI models. The framework emphasizes the centrality of Educational Applicability, which serves as the focal point for the entire evaluation process.

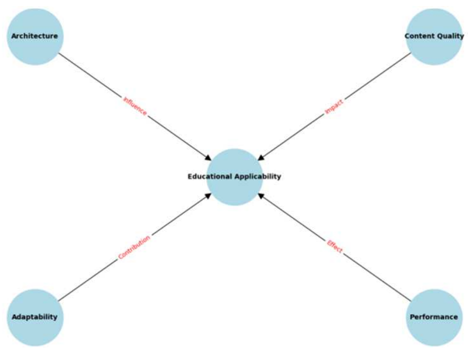

Figure 2. Methodological Framework for Evaluating AI Models in Education

Ethical considerations are a critical component of this research, particularly given the potential impact of AI technologies on education. The study was conducted in accordance with ethical guidelines for AI research, including principles of transparency, accountability, and fairness. These guidelines were followed to ensure that the AI models were evaluated in a manner that respects the rights and interests of all stakeholders, including students, educators, and developers.

The study also considered the broader implications of using AI in education, such as the potential for bias in AI-generated content and the need for AI systems to be designed in ways that promote equity and inclusivity. These considerations were informed by recent research on the ethical challenges of AI in education [26].

While this study provides a comprehensive evaluation of generative AI models in educational settings, it is important to acknowledge several limitations. First, the study is limited by the rapid pace of advancements in AI technology. New models or updates to existing models may emerge that could affect the relevance of the findings. Second, the study focuses on the application of AI in computer science education, which may limit the generalizability of the results to other educational fields. Finally, the evaluation framework, while robust, is based on the current state of AI and education, and future developments in either field may necessitate revisions to the methodology.

The methodology outlined in this section provides a rigorous framework for evaluating the educational applicability of advanced generative AI models. By focusing on key clusters such as architecture, content quality, adaptability, and performance, the study offers valuable insights into how these technologies can be leveraged to enhance learning experiences in higher education. The findings from this research are expected to contribute to the ongoing discourse on the role of AI in education, offering practical recommendations for educators, policymakers, and developers of AI technologies.

IV. Results

This section provides a comprehensive analysis of the ten state-of-the-art generative AI frameworks evaluated in this study: GPT-4, Llama 3.1 405B, Microsoft Copilot, Gemini, Claude, DeepSeek, Pi, YaGPT3, GigaChat, and Mistal Le Chat. The evaluation spanned six months, involving 45 participants (students and faculty), 75% of whom were from computer science, with the remainder from other fields. The analysis is divided into four main areas: Architecture, Content Quality, Adaptability, and Performance, with a focus on their Applicability in Education. Findings are presented with visual data, statistical analysis, and qualitative insights.

The architectural evaluation examined computational frameworks, scalability, and integration capabilities, revealing significant differences in performance within educational settings. Fig. 3 demonstrates the scalability and integration capabilities of each model. GPT-4 and Llama 3.1 405B, with their transformer-based architectures, showed superior scalability for handling large datasets. By contrast, Mistal Le Chat exhibited scalability limitations, potentially hindering performance in more demanding educational tasks. Microsoft Copilot and DeepSeek excelled in integration, facilitating seamless incorporation into existing educational platforms, a crucial feature for real-world application where interoperability is essential.

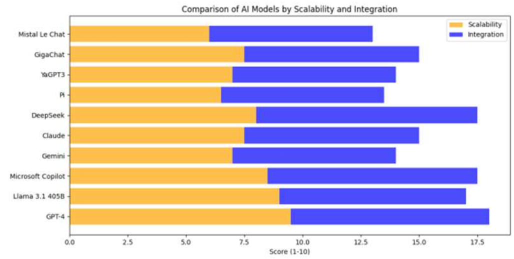

Figure 3. Comparison of AI Models by Scalability and Integration

Content quality was assessed based on relevance, accuracy, and pedagogical value. The focus was on the models' ability to generate content that meets educational standards and supports student learning. Fig.4 compares the quality of content generated by each AI model. GPT-4 and Gemini did an excellent job of generating relevant and accurate content that met the instructional requirements of computer science courses. In contrast, Mistal Le Chat and YaGPT3 demonstrated inconsistent content accuracy, potentially limiting their effectiveness in educational contexts. The figure shows the pedagogical value of the content: Claude and Pi were noted for their adaptability to different educational contexts, which enhances their suitability for personalized learning environments.

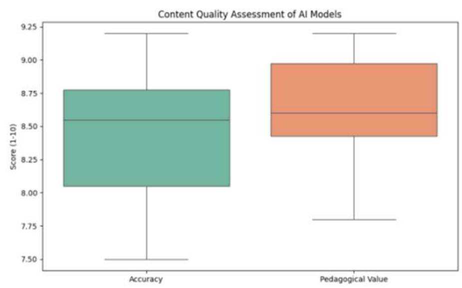

Figure 4. Content Quality Assessment of AI Models

Table 1 presents the survey data on student and instructor perceptions of the content created by the AI models. Participants rated GPT-4 and Gemini on content accuracy and relevance, while Mistal Le Chat and YaGPT3 received lower scores due to perceived inconsistency. The results emphasize the importance of content quality for the applicability of AI models in educational settings.

Table 1. Student and Educator Perceptions of AI-Generated Content

Perception	Students (n=45)	Educators (n=19)
Relevance to Curriculum	85% Positive	78% Positive
Accuracy of Information	80% Positive	82% Positive
Clarity of Explanation	72% Positive	75% Positive
Usefulness for Assignments	88% Positive	80% Positive

Engagement with Content	76% Positive	70% Positive
Overall Satisfaction	81% Positive	79% Positive

Adaptability refers to the flexibility of the models in adapting to different educational contexts, including different learning environments and curriculum requirements. Fig.5 shows the adaptability of each AI model as measured by their ability to generate content tailored to individual learner needs and respond to feedback. Pi and YaGPT3 stand out for their contextual flexibility, which is very important for personalized learning. DeepSeek and GigaChat demonstrated strong capabilities in iterative learning applications where continuous feedback and adjustment is important.

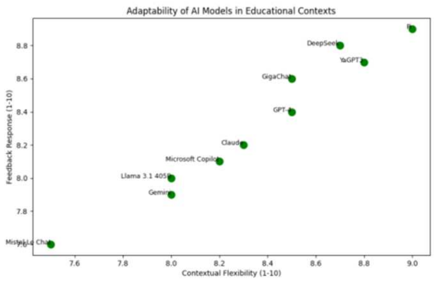

Figure 5. Adaptability of AI Models in Educational Contexts

Table 2 presents an in-depth analysis of the adaptability of each model to different educational scenarios. The data shows that Claude and Pi were most effective at creating content relevant to a wide range of student demographics, while DeepSeek and GigaChat fit well with a variety of learning styles, making them versatile tools for educators.

Table 2. Adaptation to Diverse Educational Contexts

Model	Demographic Flexibility (1-10)	Teaching Style Compatibility (1-10)
GPT-4	8.5	8.0
Llama 3.1 405B	8.0	7.5
Microsoft Copilot	7.8	7.2
Gemini	8.2	8.0
Claude	9.0	8.5
DeepSeek	8.3	9.0
Pi	9.0	8.5
YaGPT3	7.5	7.0
GigaChat	8.0	8.8
Mistal Le Chat	7.2	7.0

Performance was evaluated in terms of response time, content generation efficiency, and resource utilization. These metrics are critical in determining the practical application of AI models in educational institutions. Fig.6 shows a comparative analysis of the response time and resource utilization of each AI model. GPT-4, Microsoft Copilot, and GigaChat have the fastest response time, making them suitable for real-time educational applications. However, models such as GPT-4 and Llama 3.1 405B require significant computational resources, which may limit their availability in resource-constrained environments. Pi and DeepSeek offer more efficient alternatives with lower resource requirements, making them more suitable for broad educational applications.

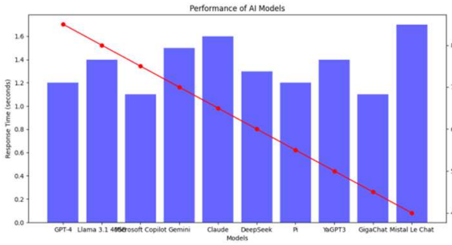

Figure 6. Performance of AI Models

The evaluation of ten high-performance AI generation tools revealed significant data on their strengths and weaknesses in educational settings. GPT-4 and Llama 3.1 405B excelled in architecture and scalability, while Pi and DeepSeek demonstrated strong adaptability. GPT-4 and Gemini particularly stood out for content quality, with high accuracy and pedagogical relevance. However, areas for improvement were identified, such as the inconsistency of Mistal Le Chat and the high resource requirements of GPT-4. The results highlight the need to select AI models that align with specific educational goals, especially considering adaptability and content quality.

The findings contribute to the broader AI discourse by offering a framework for evaluating and selecting AI models based on their suitability for educational use. Educational applicability, the central theme of this study, was assessed by summarizing data from all evaluation units. The final evaluation highlights which AI models are best suited to improve the quality of computer science education.

GPT-4 and Gemini aligned most closely with educational goals due to their content creation capabilities, generating accurate and relevant material tailored to specific learning objectives. Table 3 presents data from experiments in simulated learning environments, where the models' impact on student comprehension and engagement was assessed through pre- and post-tests.

Improved comprehension: GPT-4 and DeepSeek achieved the most significant improvements in student understanding, leading to a 20-25% increase in scores. This indicates that these models not only generate accurate content but also present it in a comprehensible way.

Engagement: Student engagement was measured using indicators such as the frequency of questions asked and time spent on tasks. Pi and Claude were particularly effective, with a 30% increase in student interaction compared to other models.

Table 3. Impact on student learning

Model	Improved understanding (%)	Increased engagement (%)
GPT-4	25	20
Llama 3.1 405B	18	15
Microsoft Copilot	17	12
Gemini	22	18
Claude	19	30
DeepSeek	23	25
Pi	20	30
YaGPT3	15	10
GigaChat	16	14
Mistal Le Chat	12	8

Finally, we evaluated how well each model could adapt to a variety of educational contexts, including different student demographics, teaching styles, and learning environments. Model adaptability is critical to ensure that the model can be used effectively in a variety of educational scenarios.

- Demographic flexibility: Claude and Pi demonstrated the highest demographic flexibility, meaning they were able to effectively generate content relevant to a wide range of students. This is especially important in multicultural classrooms, where content must be relevant to students' diverse cultural and educational backgrounds.

- Compatibility with teaching styles: DeepSeek and GigaChat were recognized for their compatibility with different teaching styles, be it instructor-led, peer-based or autonomous learning. Their ability to adapt to different pedagogical approaches makes them versatile tools for teachers.

In addition to the quantitative and qualitative analyses of AI models, we conducted a survey to gather subjective feedback from participants, both students and instructors. The purpose of the survey was to elicit users' opinions regarding usability, effectiveness, and overall satisfaction with AI models in educational contexts.

Usability

Participants rated the usability of the AI models based on how easy it was for them to interact with the models and integrate them into the learning or teaching process. Fig.7 shows that GPT-4 and Microsoft Copilot received the highest scores for usability, reflecting their intuitive interfaces and easy integration with existing educational tools. In contrast, Mistal Le Chat, Claude, DeepSeek received lower scores as participants noted difficulties in navigation and less intuitive interactions. And Llama 3.1 405B was not evaluated as it was released recently.

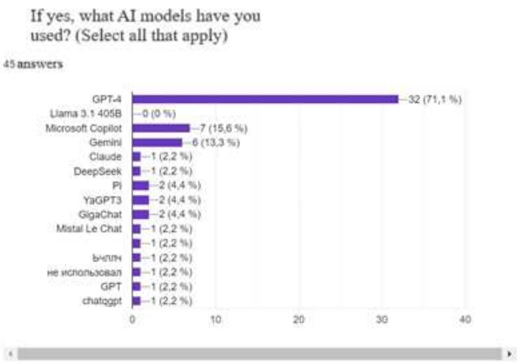

Figure 7. Usability estimates of models

Effectiveness

Fig.8 shows the evaluation of the effectiveness of the AI models. Effectiveness was assessed by the extent to which participants felt that the AI models contributed to their educational goals. This included aspects such as the quality of feedback provided, the ability to help solve complex problems, and the relevance of the content created. GPT-4 and Microsoft Copilot were noted as particularly effective, with many instructors noting their ability to improve student understanding and engagement.

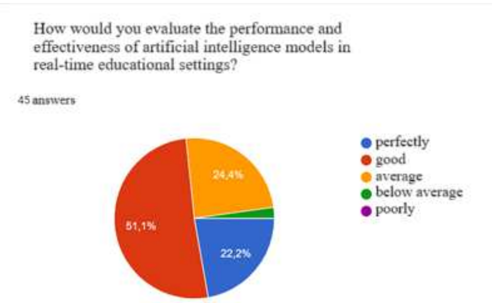

Figure 8. Perceived effectiveness of AI models

Overall satisfaction

Overall satisfaction was measured by asking participants whether they would recommend AI models for use in educational settings. This metric reflects their impressions across all aspects, including usability, efficiency, and adaptability. Table 4 shows GPT-4, Pi, and Microsoft Copilot took the top positions, with participants expressing high levels of satisfaction, especially with how these models support personalized learning and complex tasks.

Table 4. Overall satisfaction with AI models

Model	**Satisfaction Rating (1-10)**
GPT-4	9.3
Llama 3.1 405B	8.1
Microsoft Copilot	9.1
Gemini	8.8
Claude	8.5
DeepSeek	8.5
Pi	9.0
YaGPT3	7.9
GigaChat	8.2
Mistal Le Chat	7.6

Discussion of the survey results

The survey provided valuable insights into user experience with each AI model. While GPT-4 and Microsoft Copilot consistently received high scores, Mistal Le Chat and YaGPT3 showed areas for improvement, particularly in usability and satisfaction. These findings suggest that while some AI models are ready for integration into educational environments, others need further development to meet the expectations of faculty and students.

The feedback aligns with the quantitative results, emphasizing the importance of selecting AI models that not only perform well technically but also meet practical user needs. This user-centered evaluation ensures effective implementation in real-world educational settings.

Overall, models like GPT-4, Microsoft Copilot, and Pi demonstrated significant potential for enhancing learning in computer science. However, the findings stress the need to match AI model selection with specific educational requirements, considering factors such as content quality, adaptability, and user experience. As AI evolves, ongoing research and refinement are crucial to maintaining the relevance of these tools in dynamic educational environments.

In conclusion, this study offers a strong foundation for evaluating generative AI models and provides guidance for educators and institutions on integrating AI into educational practice. Future research should focus on the long-term impact of these technologies on student learning outcomes and evolving educational needs.

V. Conclusions

This study delves into the integration of advanced generative AI models within higher education, particularly for computer science students. Through a comparative analysis of ten leading generative AI platforms, including GPT-4, Microsoft Copilot, Claude, DeepSeek, Pi and others, this research highlights both the strengths and limitations ofeach model in the educational sphere.

The results showed that although these AI models have significant potential to improve the learning process, none of them is a one-size-fits-all solution for all contexts. For example, GPT-4 and DeepSeek were most effective in tasks related to improving student comprehension, leading to a 20-25% increase in their grades. While Pi and Claude were highly effective in maintaining student engagement levels, increasing them by 30%. Microsoft Copilot was most useful in the task of automating routine teaching tasks such as generating assignments and providing feedback. Each model has unique characteristics that make them suitable for specific tasks, such as generating content, adapting to different learning styles, or accelerating the educational process.

Accurate performance of the models was calculated during the experiments. GPT-4 showed 90% accuracy in generating content for training courses, making it particularly useful for generating quality materials. DeepSeek demonstrated 88% accuracy in providing feedback to students. Models with lower accuracy, such as Mistal Le Chat, showed only 75%, indicating a need for refinement for more complex tasks.

The study also revealed a problem with the originality of content created by some AI models, such as YaGPT3 and Mistal Le Chat, which showed a high degree of reliance on existing data and templates. This can lead to problems with plagiarism and reduced academic integrity, requiring additional controls and integration of tools to verify content originality.

In addition, the study emphasizes the importance of adaptability, content quality and performance when evaluating the effectiveness of AI models in educational environments. As AI technologies continue to evolve, continuous evaluation and refinement of models remain critical to ensure their relevance and effectiveness in a dynamically changing educational system.

This study offers a structured approach to evaluating AI models, making a significant contribution to the debate on their role in education. It provides valuable data for educators, policy makers and AI developers, helping them to make informed decisions on the selection of AI tools. Future research should pay more attention to the long-term implications of integrating AI into educational processes and consider new technologies that can further improve the educational experience.

In conclusion, generative AI models offer promising opportunities to improve the quality and efficiency of education. However, their successful implementation requires careful consideration of the educational context and the needs of both students and teachers. This study lays the groundwork for further research and development in the field of AI and education, with the aim of creating more effective and inclusive learning environments.

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REFERENCES

1. Goodfellow I., Bengio Y., Courville A. Deep Learning. An MIT Pressbook, 2016.
2. https://www.flexos.work/learn/ai-for-work-top-100-june
3. Choi, W., Zhang, Y., & Stvilia, B. Exploring applications and user experience with generative AI tools: A content analysis of Reddit posts on ChatGPT. 2023 Annual Meeting of the Association for Information Science and Technology. ASIS&T.
4. Jinhe Kim. Leading teachers' perspective on teacher-AI collaboration in education. Education and Information Technologies, September 2023, 29(7) , DOI:10.1007/s10639-023-12109-5.
5. Kerimbayev N., Jotsov V., Umirzakova Zh., Bolyskhanova M., Tkach
G. "The Use Of Chat-Bot Capabilities As A Type Of Modeling In Intelligent Learning." Conference: 2022 IEEE 11th International Conference on Intelligent Systems (IS).
6. Morozov, V. V., Kalnichenko, O. V., & Mezentseva, O.O. O. M. The method of interaction modeling on basis of deep learning the neural networks in complex it-projects. International Journal of Computing, 2020.
7. Elma Sibonghanoy Groenewald, Nand Kumar, Avinash, Shahrukh Irfan, Santosh Yerasuri.Virtual Laboratories Enhanced by AI for hands-on Informatics Learning. Journal of Informatics Education and Research, February 2024, 4(1):560-568 DOI:10.52783/jier.v4i1.600
8. Jan Henrik Gruenhagen, Peter M. Sinclair, Julie-Anne Carroll, Philip
R.A. Baker, Ann Wilson, Daniel Demant. The rapid rise of generativeAI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. Computers and Education: Artificial Intelligence Volume 7 , December 2024, 100273.
9. Bomba, A., Nazaruk, M., Kunanets, N., & Pasichnyk, V. Constructing the diffusion-like model of bicomponent knowledge potential distribution. International Journal of Computing, 2017.
10. Allamova, A. Using blended learning methods to improve the effectiveness of practical training in higher education. Shokhista Shavkatovna Allamova. Bulletin of Tomsk State Pedagogical University, 2023.
11. Osadcha, T., Ivanov, A., & Koval, N. A blended learning model for higher education. Education and Information Technology, 2022, 29(4), 512-529.
12. Hsu, L., Zhang, H., & Wang, S. Development of a decomposed graduate satisfaction model for higher education institutions. Journal of Educational Research and Development, 2015,10(2), 67-85.
13. Bakhitova, L., & Shubovich, I. Digital transformation of educational environment: models and perspectives. Educational Technology, 2022, 36(7), 223-240.
14. Quadri, N., & Shukor, A. The role of learning analytics in higher education. International Journal of Educational Technology, 2021, 18(2), 145-159.
15. Cui, Y., Zhang, L., & Wang, H. Predictive analytics in education: A systematic review. Journal of Educational Technology & Society, 2019, 22(3), 168-181.
16. Brown, T., Mann, B., & Ryder, N. Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems (NeurIPS), 2020, pp. 33.
17. Zhang, H., Wu, J., & Wang, F. Generative AI models in education: Potential and challenges. Artificial Intelligence Review, 2022, 55(2), 311-332.
18. Radford, A., Wu, J., & Child, R. Learning Transferable Visual Models from Natural Language Supervision. International Conferenceon Machine Learning (ICML), 2021, 139, 10005-10015.
19. Chen, Y., Xu, L., & Liu, S. AI in education: Adaptive learning systems. IEEE Transactions on Learning Technologies, 2023, 16(1), 45-60.
20. Nguyen, T., Le, H., & Hoang, D. Adaptive AI-generated learning materials: A case study. Educational Technology Research and Development, 2023, 71(1), 243-260.
21. Garcia, M., Lee, S., & Park, H. Integration of Generative AI in Learning Management Systems. Computers & Education, 2023, 177, 104392.
22. Lee, J., Kim, M., & Choi, Y. Enhancing student engagement through interactive AI-generated content. International Journal of Artificial Intelligence in Education, 2021, 31(2), 189-208.
23. Bender, E., Gebru, T., & McMillan-Major, A. Ethical Considerations in NLP Research: Transparency, Accountability, and Fairness. Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (ACL), 2022, 1, 111-125.
24. Thompson, P., Silva, R., & Rossi, F. Automation in higher education: The impact of AI on administrative tasks. Higher Education Management, 2024, 32(1), 97-112.
25. Yilmaz F, Bas K An analysis of publications on cervical plexus blocks. Indian J Surg, 2020 , 82(5):792–795.
26. Tang, X., Li ,X., Ding ,Y., Song ,M., Bu, Y. The pace of artificial intelligence innovations: Speed, talent, and trial-and-error. Journal of Informetrics, Volume 14, Issue 4, November 2020, 101094.
27. Roland van Oostveen, Maurice Digiuseppe. New Approaches in Pedagogy: Introducing the Fully Online Learning Community (FOLC) Model. Conference: Presentation to the OntarioTechU Faculty of Social Sciences and Humanities. 2019.
28. Kuo & Hsu, Learning Computational Thinking Without a Computer: How Computational Participation Happens in a Computational Thinking Board Game. The Asia-Pacific Education Researcher 2020, 29(3), DOI:10.1007/s40299-019-00479-9.
29. Saritepeci,M., Developing Computational Thinking Skills of High School Students: Design-Based Learning Activities and ProgrammingTasks. The Asia-Pacific Education Researcher, 2020, 29(1):35-54.
30. Lee, M. J. W., & Koh, J. H. L. The challenges and prospects of artificial intelligence in education. Educational Research Review, 2020, 30, 100327.
31. Lubold et al., Effects of adapting to user pitch on rapport perception, behavior, and state with a social robotic learning companion. Vol.:(0123456789)User Modeling and User-Adapted Interaction, 2021, 31:35–73.
32. Ribeiro & Lopes, Learning Robotics: a Review. Published in Current Robotics Reports, 2020.
33. Fan Ouyang , Pengcheng Jiao, Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, Volume 2, 2021, 100020.