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Conceptual Article

Artificial intelligence in mathematics education: The good, the bad, and the ugly

Oluwaseyi A. G. Opesemowo[1] and Mdutshekelwa Ndlovu[2]

[1]*University of Johannesburg, South Africa (ORCID: 0000-0003-0242-7027)*
[2]*University of Johannesburg, South Africa (ORCID: 0000-0002-1187-0875)*

Integrating Artificial Intelligence [AI] into mathematics education offers promising advancements and potential pitfalls. Striking a balance between AI-driven developments and preserving core pedagogical principles is critical in the teaching and learning environment. AI has emerged as a transformative force in various fields, including education. In the realm of mathematics education, AI technologies offer a spectrum of potential benefits (including personalize instruction, adaptive assessment, interactive learning environments, and real-time feedback, among others) and challenges (such as lack of creativity and problem-solving skills, inability to explain reasoning, bias in data and algorithms, absence of emotional intelligence and data privacy and security concern etc). This conceptual study used autoethnography as the methodology and qualitative content approach to analyze data. The study discussed historical background of AI and considered ethical issues around AI. It was concluded that the journey to harness the full potential of AI in mathematics education requires careful navigation of the good, the bad, and the ugly aspects inherent in this technological evolution.

Keywords: Artificial intelligence; Big data; ChatGPT; Machine learning; Mathematics education

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1. Introduction

Artificial intelligence [AI] is a multidisciplinary field that focuses on developing intelligent machines that can perform tasks typically performed by humans (Mohamed et al., 2022). AI involves studying, designing, and developing algorithms and systems that can make decisions based on what they perceive and experience in their environment. Machine learning, natural language processing, computer vision, robotics, expert systems, and other subfields are all part of AI (de-Lima-Santos & Ceron, 2021; Deng & Liu, 2018). These subfields use various approaches and strategies to allow machines to emulate or simulate human cognitive processes. An AI seeks to create intelligent systems that can perform tasks autonomously and adapt to various environments (Ayanwale et al., 2024; Opesemowo & Adekomaya, 2024; Weber & Schutte, 2019). Understanding natural language, detecting, and interpreting visual and auditory information, making predictions, solving problems, and even displaying creativity and social intelligence are all examples of abilities.

Address of Corresponding Author

Oluwaseyi A. G. Opesemowo, PhD, Department of Science and Technology Education, Faculty of Education, University of Johannesburg, P.O. Box 2006, South Africa.

oopesemowo@uj.ac.za

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AI systems rely on data, algorithms, and computer power to learn from experience, spot patterns, and make judgments (Miller & Brown, 2018). Machine learning is a critical component of AI (Gaudet, 2022), and it involves creating algorithms that allow machines to learn from data and improve their performance over time without being explicitly programmed. Deep learning is a form of machine learning which employs neural networks with numerous layers to process and evaluate complicated data. The origin of AI may be traced back to the mid-twentieth century when pioneers such as Alan Turing, John McCarthy, Marvin Minsky, and others laid the groundwork for the discipline. The Dartmouth Conference in 1956 was a turning point in AI history, as it was here that the phrase AI was born (McCarthy et al., 2006).

According to Haenlein and Kaplan (2019), AI has undergone various progress and setbacks over the years. The discipline went through an "AI winter" in the 1970s and 1980s, marked by low interest and slow growth. However, the advent of big data necessitated the development of big data analytics (algorithms and computer applications) for assisting with expedited decision-making (Jin et al., 2022; Liu et al., 2022), improved computing power, and advances in machine learning, AI has witnessed a rebirth in the twenty-first century (Sevnarayan, 2024; Williamson, 2017). AI applications have permeated various industries and disciplines, including education, healthcare, banking, transportation, gaming, and customer service. Apple's Siri, Amazon's Alexa, ChatGPT, and Google Assistant have become commonplace AI-powered digital assistants that affect our decision-making and preferences.

AI can transform several industries, including education. In the field of mathematics education, AI offers novel solutions that have the potential to alter how students learn, teachers teach, and educational institutions operate. The influence of AI on mathematics education is significant in personalized learning, from individualized learning experiences to sophisticated problem-solving tools. One of the primary benefits of AI in mathematics education is individualized learning. AI-powered platforms can assess individual students' strengths and weaknesses, learning styles, and rates of cognitive growth (Jaiswal & Arun, 2021; Owan et al., 2023; Upadhyay & Khandelwal, 2019). This data-driven method enables educators to adjust learning materials and exercises to the needs of individual students, thus maximizing engagement and optimizing understanding. In the words of Liu et al. (2022), researchers investigating mathematics education and personalized learning are more concerned with developing school pupils' complete subject abilities. The deep integration of AI, big data technology, and education is projected to play a significant role in education evaluation reform. The Modular Object-Oriented Dynamic Learning Environment (Moodle) can be utilized to create the school mathematics curriculum in a targeted manner to scientifically guide students in selecting concepts to improve and enhance their mathematical competence.

2. Historical Background of Artificial Intelligence

AI has an intriguing past that dates back ages. The history of AI began in the mid-twentieth century and has witnessed substantial improvement and discoveries over the years. This section discusses the rundown of the history of AI.

2.1. Early Research (1950s-1960s)

During the early research period of AI in the 1950s and 1960s (in the last millennium), the field was defined by lofty aims, game-changing concepts, and foundational achievements that lay the platform for later progress of AI. It established the field's theoretical foundations and conceptual framework. While early AI systems had limited capabilities and encountered problems, they laid the groundwork for developing more advanced AI techniques in the following decades. The emphasis on symbolic reasoning, logic, and problem-solving throughout the era prepared AI to evolve into diverse subfields such as machine learning, natural language processing, and expert systems. The 1950s and 1960s were a time of pioneering investigation, with researchers laying the framework for future advances in AI. At the same time, the era was fraught with difficulties, which resulted in reduced financing. Haenlein and Kaplan (2019) admit that this was the AI winter. The concepts and advancements during this period prepared the stage for the eventual comeback of AI research and its revolutionary impact on numerous industries in the following decades. However, during this period, the Dartmouth conference was organized to rekindle interest.

The Dartmouth Conference, held in the summer of 1956, catalyzed the establishment of AI (Barron, 2023; Haenlein & Kaplan, 2019) as a discipline. Those who participated would go on to lead AI research for decades. Many of them projected that a machine as clever as a human would exist within a generation, and they were paid millions of dollars to make this vision a reality (Anyoha, 2017; Newquist, 1994). John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon coined AI and laid the groundwork for the discipline at this meeting (McCarthy, 1998). Symbolic techniques and logic-based reasoning dominated early AI research. Mathematical logic (algorithmic thinking) was the dominant approach in the early years of AI research. The researchers wanted to create machines that could solve problems using logical deduction and rule-based systems. This strategy emphasized formal languages, algorithms, and mathematical representations.

2.2. The AI Winter (1970s-1980s)

AI research encountered substantial setbacks in the 1970s and 1980s despite early enthusiasm. There was a dearth of finance and high expectations; therefore, progress was slower than projected. This period, coined the "AI winter" by McCarthy in 1955 (McCarthy et al., 2006), saw reduced interest and slower growth in the discipline. The word initially surfaced in 1984 as the subject of a public debate at the annual meeting of the Association for the Advancement of Artificial Intelligence (AAAI, then known as the "American Association of Artificial Intelligence"). It is a chain reaction that began with pessimism in the AI community, followed by pessimism in the press, significant budget cuts, and the cessation of serious research (Crevier, 1993). At the summit, two prominent AI researchers (Roger Schank and Marvin Minsky) who had survived the "winter" of the 1970s warned the business community that enthusiasm for AI had waned in the 1980s and that disappointment was unavoidable. Three years later, the billion-dollar AI sector crumbled (Crevier, 1993). The AI winter was occasioned by the loss of faith in exaggerated claims by developers, excessively high expectations from end users, and excessive media promotion. Despite its reputational vicissitudes, AI has continued to develop new and profitable technologies. In 2002, AI researcher Rodney Brooks bewailed the myth that AI had failed and argued that AI was thriving.

Batty (2018) bemoaned that many observers still believed that the AI winter was the end of the story and that nothing had come of the AI field since. Thousands of AI applications are now deeply suppressed in every industry's infrastructure. Since the low point in the early 1990s, enthusiasm and optimism for AI have revived. In 2012, research and corporate interest in AI (particularly the sub-field of machine learning) led to a substantial increase in funding and investment, resulting in the current (as of 2023) AI boom.

2.3. Expert Systems and Knowledge-Based AI (1980s-1990s)

Expert systems use human expertise and knowledge of the system environment to solve the problem (Kusiak & Chen, 1988). During the 1980s and 1990s, the emphasis of AI research turned toward expert systems and knowledge-based AI. Expert systems were prevalent throughout this time, aiming to capture and utilize human expertise to tackle complex issues in specific fields. Knowledge-based AI aims to represent and reason in an organized way systems to execute tasks requiring expertise and decision-making abilities speedily. Here are some essential characteristics of expert systems and knowledge-based AI in this era. They include developing expert systems and AI programs that mimic the decision-making abilities of human experts in specific subjects. They comprise two parts: a knowledge base containing facts and rules and an inference engine that uses the knowledge/information to reason and make judgments. Expert system development included knowledge acquisition, in which human experts provided the essential information to build the knowledge base. Also, the Expert systems were mainly rule-based, using "if-then" logic to guide their reasoning. These rules encoded domain experts' experience, and the inference engine used them to draw inferences and make recommendations. Integrating expert systems with other AI approaches: Researchers (Gaines, 1987; Gevarter, 1984; Kusiak & Chen, 1988) try integrating expert systems with different AI approaches, such as machine learning. Some systems could enhance performance by integrating rule-based or logic-mathematical reasoning with learning techniques.

Knowledge Engineering: During this period, knowledge engineering emerged as a critical discipline. It entailed acquiring, representing, and organizing knowledge for expert systems. Domain experts and knowledge engineers cooperated to effectively encode their expertise into the system. Despite early triumphs, expert system creation and maintenance proved more complex and costly than anticipated. Overinflated expectations surrounding AI in the 1980s resulted in a period known as the "AI winter," in which interest and investment in AI research plummeted due to unfulfilled promises and dashed expectations.

Change to other AI paradigms: By the end of the 1990s, the focus had switched to alternative AI paradigms, such as neural networks (e.g., as in Python) and statistical techniques like Bayesian (or probabilistic) networks. These approaches demonstrated improved capabilities in dealing with uncertainty and learning from data, leading to the late 1990s and early 2000s revival of AI.

2.4. Machine Learning and Neural Networks Resurgence (1990s-2000s)

AI had a renaissance in the 1990s and 2000s (advent of the new millennium), owing primarily to advancements made in machine learning (Kompa et al., 2022) and revived interest in neural networks. This period saw a substantial shift in AI research as academics and practitioners experimented with new techniques and procedures, resulting in successes in various disciplines. In this period, there were some fundamental developments in the comeback of machine learning and neural networks. These are:

Machine Learning and Statistical Approaches: Machine learning gained prominence during this time, and researchers began investigating statistical approaches to AI problems. Bayesian networks, support vector machines [SVM], decision trees, and ensemble approaches such as random forests became prominent (Faisal et al., 2018; Teles et al., 2021; Trivedi et al., 2020). These approaches opened new data analysis and prediction pathways, paving the way for data-driven AI systems.

Big Data and Processing Power: The availability of large-scale datasets (e.g., education research data, admission, and enrollment data) and greater processing power (e.g., computational) has tremendously impacted the revival of machine learning and neural networks. Researchers can now train more complicated models on massive volumes of data, resulting in better performance in various AI activities. These AI activities can also be used in mathematics education such that complex mathematics tasks can be taught using AI tools (such as Scikit learn, Tensorflow, Theano, PyTorch, and Google ML) to enhance students' performance and make mathematics exciting and enjoyable for students.

The Rise of Data-Driven AI: With the resurrection of machine learning, attention has switched to data-driven AI systems (Akter et al., 2021; Wen et al., 2021). Instead of mainly depending on handmade rules and expert knowledge, AI systems began learning patterns and regulations directly from data, making them more adaptive and capable of dealing with complicated and unstructured data. The expansion of machine learning and neural networks in the 1990s and 2000s laid the groundwork for the AI revolution. The advances during this period established the foundation for creating ever more advanced AI models, leading to their widespread adoption and incorporation into different facets of our daily lives. This significant progress in AI would have been a mirage without mathematics. Richard et al. (2022) alleged that AI, however, depends heavily on mathematics (such as logic and set theory, calculus, probability and statistics, linear algebra, and optimization, etc.) since it provides the formal language and tools for expressing and understanding the concepts and algorithms that drive the AI technology.

2.5. Big Data and Deep Learning (2010s)

AI significantly progressed in the 2010s due to the development of Big Data and Deep Learning (Ashta & Herrmann, 2021; Batra et al., 2018; Richard et al., 2022; Tsay & Patterson, 2018; Zhu, 2020). Both technologies - Big Data (e.g., forecasting customer behavior and product strategies in marketing, descriptive statistics assisting in GPS navigation, traffic density, weather forecasts in transportation, market data in business, etc.) and Deep Learning (e.g., Long short-term memory network, Radial function networks, Multilayer Perceptrons, Self-organizing Maps, Convolutional Neural Networks, etc.) were critical in altering industries, revolutionizing data analysis, and developing robust AI systems. The availability of massive volumes of data and increased processing power constituted a watershed moment in AI. Deep learning, a subset of machine learning (Gaudet, 2022), has gained popularity due to its capacity to analyze vast amounts of data and derive valuable insights. Deep neural networks have significantly advanced in various fields, including image and speech recognition. With the rise of virtual (digital) assistants and recommendation systems, AI applications began to permeate daily life.

Big Data refers to the massive amount of structured and unstructured data generated by various sources, including social media, Internet of Things [IoT] devices, online transactions, sensors, etc. (Azad et al., 2020; Kumari et al., 2019). The distinguishing qualities of Big Data are typically defined as vast amounts of largely quantitative data, rapid data generation, and a variety of data types, including text, photos, videos, and so on. During the 2010s, Big Data was critical to the advancement of AI (Duan et al., 2019; Javaid et al., 2021). AI algorithms, particularly those in machine learning (e.g., algebra, calculus, artificial neural networks, logistic regression, linear regression) and deep learning, rely on massive volumes of data to discover patterns, make predictions, and enhance performance. AI models could be trained on representative and diversified samples with access to massive datasets, resulting in higher generalization and more accurate predictions. In contrast, Deep learning is a component of machine learning that involves training artificial neural networks with numerous layers to learn hierarchical data representations automatically. These neural networks were developed based on the structure and function of the human brain.

In the 2010s, there was a significant synergy between Big Data and Deep Learning, resulting in the availability of vast volumes of data that assisted Deep Learning model training (Shah, 2016; Tolk, 2015). Deep learning, in turn, provided a robust framework for evaluating and extracting insights from Big Data. The convergence of these technologies resulted in substantial advances in AI applications spanning from improved recommendation systems to autonomous vehicles and cutting-edge medical diagnosis. The 2010s was a turning point in AI history, with Big Data and Deep Learning sparking an upsurge in the field (Nguyen, 2023). These technologies provided the groundwork for the AI revolution, which is still shaping our world today, with AI becoming increasingly important.

AI has made significant strides and impacts in transforming various aspects of human life, including industries and education. It offers great promise, but it also presents challenges and potential drawbacks. This article explores the positive impact of AI in mathematics education, examines the possible negative aspects, and discusses the ethical considerations associated with its implementation.

3. Methodology

This study adopted an autoethnography research approach, allowing the researchers to capture the intricacies of AI implementation in real-world educational contexts. Autoethnography is a relatively new paradigm that offers reflective narratives to elucidate the researcher’s experiences and analyze cultural beliefs, practices, and social experiences that influence our identities (Allen, 2015). The data were gathered from secondary sources, specifically archival AI studies, and analyzed using qualitative content analysis. The researchers found that autoethnography provided a unique perspective on the challenges and successes of AI implementation in mathematics education, highlighting the importance of considering the ethical use of AI technologies. The qualitative content analysis of archival AI studies provided a thorough understanding of the current AI landscape in education and the historical context of AI.

4. AI: The Good

AI can potentially enhance (The Good) mathematics learning experiences in several ways. These include:

1. *Personalized Instruction*: AI algorithms can analyze student data and provide personalized instruction based on individual needs, learning styles, and performance in mathematics. This tailored approach allows students to progress at their own pace, fill knowledge gaps, and receive targeted support, resulting in improved learning outcomes.

2. *Adaptive Assessment*: AI-powered assessment tools can offer adaptive testing, dynamically adjusting the difficulty of questions based on students' responses. This approach provides accurate assessments, identifies areas of weakness, and offers tailored feedback, allowing educators to support student progress better (Davis, 2023). Adaptive assessment solutions powered by AI can generate personalized mathematics questions and examinations for each student based on their knowledge level and progress. These tests adjust the difficulty of questions in real time, ensuring that students are suitably pushed and tested, resulting in more accurate assessments of their mathematical abilities.

3. *Interactive Learning Environments*: AI technologies like virtual simulations and gamification create engaging learning environments (Bennani et al., 2022; Kumar, 2022). These tools promote active participation, problem-solving, and critical thinking skills, making mathematics more accessible and exciting for students.

4. *Grading Automation*: AI can automate the grading of mathematics assignments and assessments, saving teachers time and allowing them to focus on other areas of teaching practices (Owan et al., 2023). Grading automation in mathematics education is a groundbreaking AI program that automates the evaluation and feedback process for assignments and assessments. Grading mathematics assignments has always been time-consuming for teachers, especially when dealing with many students and complex mathematical problems. However, AI-powered grading systems make this process more efficient and accurate, benefiting educators and pupils.

5. *Real-Time Feedback*: AI-based math applications (such as Photomath, Soratic, Mahtway, Maple Calculator, and Microsoft Math Solver) can provide immediate feedback on students' math problem solutions. This quick feedback assists students in identifying and correcting errors, so reinforcing learning and developing problem-solving skills.

6. *Augmented Reality Applications*: Through augmented reality [AR] applications, AI can improve mathematics instruction. AR can bring mathematical concepts to life by superimposing digital information on the real-world environment, making abstract ideas more tangible and understandable for learners without leaving the classroom (Bower, 2014). Students, for example, can utilize augmented reality to visualize geometric forms in their surroundings or to explore 3D models of mathematical concepts, developing deeper learning and spatial thinking. Examples of AR applications include Google Expeditions, Quiver, and Anatomy 4D.

7. *Teacher Professional Development:* AI can help mathematics teachers with individualized professional development. AI systems can offer customized training modules, workshops, and resources to improve teachers' instructional skills and pedagogical approaches by analyzing their performance and areas for growth.

8. *Reinforcement Learning for Math Tutoring*: Reinforcement learning algorithms powered by AI can continuously optimize tutoring tactics for math instruction. AI algorithms adjust and refine their

instructional approaches based on the effectiveness of previous exchanges when students interact with the tutoring system.

9. Data Analytics for Teachers: Data analytics powered by AI can assist teachers in identifying learning gaps, patterns, and trends in their classes. Teachers may track individual and group performance, identify misconceptions, and tailor educational tactics to meet unique student requirements.

10. Online Math Competitions: AI can power online math competitions and challenges, providing participants with adaptable and demanding problem sets. These tournaments establish a competitive yet enjoyable environment, motivating children to thrive in mathematics and demonstrate problem-solving abilities.

11. ChatGPT: ChatGPT is an abbreviation for Chat Generative Pretrained Transformer, which OpenAI developed in November 2022. Even though ChatGPT is still in the infancy stages of development, it can replace the writing process, as electronic database search engines have replaced card catalogues. On the other hand, some instructors consider ChatGPT to be a tool that includes search engines, editing software, statistical software, and reference management systems (Frith, 2023). It is a sophisticated chatbot that responds to questions using AI and natural language processing. It also responds to requests to generate text or graphics by training models on data from the internet, books, papers, and other sources (OpenAI, 2022). ChatGPT is a text-based AI platform powered by AI that uses machine learning to automate repetitive operations and boost client engagement. It employs natural language processing algorithms to comprehend human-like text and generate accurate responses to basic inquiries. ChatGPT provides a wide range of benefits (such as timesaving, content creation quality, human-like rejoinders with follow-up questions, virtual assistance, learning exploration, search engine optimization, and generate mathematics assessment questions, etc.) by integrating machine learning technology, which can significantly boost users' satisfaction.

5. AI: The Bad and The Ugly

While the benefits are significant, AI has challenges and limitations in mathematics education.

1. Lack of Creativity and Problem-solving Skills: Mathematics education is more than just answering routine problems; it is also about cultivating creativity and problem-solving abilities. AI algorithms are excellent at pattern detection and optimization but lack human-like creativity (Benvenuti et al., 2023; Marrone et al., 2022) and the ability to think outside the box. As a result, they may be less effective at encouraging pupils to try new problem-solving methods. In addition, when confronted with real-life workplace situations in which critical and creative thinking is needed, the lack of creativity in AI will invariably have detrimental effects on learners when entirely dependent upon it.

2. Inability to Explain Reasoning: AI models, particularly complicated ones like deep neural networks, frequently operate as "black boxes," providing solutions without reason. Explanations are essential for students to understand the logic behind answers in a mathematics classroom thoroughly. Developing AI models that provide transparent and interpretable explanations is imperative to improve learning.

3. Overemphasis on Computational Skills: Since AI can automate calculations, overemphasizing computational abilities and basic procedures may discourage learners from engaging their brains when dealing with routine problem-solving tasks. While these abilities are necessary, a well-rounded mathematics education should emphasize conceptual understanding, mathematical reasoning, critical thinking, metacognition, and mathematical applications in real-world contexts (e.g., horizontal and vertical mathematization, Freudenthal, 1991) and other areas where AI cannot fully replace human instruction.

4. Bias in Data and Algorithms: AI models are trained on historical data, which may contain accidental biases and deliberate (normative) prejudices against minority and vulnerable groups.

These biases may colour the decision-making process of AI, resulting in inaccurate assessments of student achievement or favouring certain teaching styles over others. To offer equitable learning opportunities for all pupils, bias in AI for mathematics teaching must be addressed (Davis, 2023).

5. *Lack of Emotional Intelligence*: Mathematics education entails more than just delivering knowledge; it also entails creating a welcoming learning atmosphere. Because AI lacks emotional intelligence (Khanam et al., 2019; Kumar & Sharma, 2012;), it cannot provide the same level of empathy, encouragement, and emotional support human teachers can.

6. *Data Privacy and Security Concerns*: AI-powered math education platforms collect and analyze student data to deliver individualized learning experiences, creating data privacy and security concerns (Huang et al., 2022; Lee & Ahmed, 2021).

7. *Dependency on AI for Problem-solving*: Overreliance on AI technologies for problem-solving may stifle pupils' ability to think independently and solve problems critically (Marzuki et al., 2023). Students may fail to solve non-routine problems or apply their knowledge in unusual or non-standard settings if they increasingly rely on AI for solutions.

8. *Lack of Real-time Interaction*: Traditional classroom environments encourage direct interaction between students and teachers, allowing teachers to assess students' comprehension and alter their instruction accordingly. AI may lack the real-time reaction required for dynamic classroom interactions, making it impossible to properly handle urgent inquiries or concerns (Almaiah et al., 2022).

9. *Oversimplification of Concepts*: AI algorithms may provide quick answers and solutions without fostering deep conceptual understanding. Students may become overly dependent on AI for problem-solving without fully comprehending the underlying mathematical principles.

10. *Inequitable Access*: AI implementation may exacerbate existing disparities in access to technology and resources, creating a digital divide between students with access to AI-powered tools and those without (Božić, 2023; Estrellado & Miranda, 2023; Tan & Chen, 2023). Equitable access to AI technologies is crucial for fair and inclusive mathematics education.

11. *Loss of Critical Thinking Ability*: Students may miss opportunities to acquire critical thinking and problem-solving skills if they rely extensively on AI tools to solve mathematical problems and deliver answers. They may develop a habit of following prescribed processes without fully comprehending the underlying concepts. Critical thinking and problem-solving abilities are essential components of mathematics instruction (Dolapcioglu & Doğanay, 2022; Insorio & Librada, 2021; Leader & Middleton, 2004). They entail assessing problems from multiple perspectives, considering numerous approaches, and using logical reasoning to arrive at analytic solutions. Students who rely on AI programs to deliver quick mathematical solutions may miss out on the opportunity to engage in this cognitive process. Consequently, their ability to independently assess and solve complex problems may be compromised. Furthermore, critical thinking, which encourages students to be innovative in problem-solving, frequently entails investigating unusual techniques and connecting seemingly unrelated concepts. AI systems are typically programmed to follow established algorithms, which may thwart learners from thinking creatively and exploring alternate answers. Mathematics education is at risk of long-term problems if critical thinking skills are not developed. Students who have not been taught to think critically may struggle in higher-level mathematics courses or when confronted with real-world issues that do not fit into established procedures (Alam, 2022).

12. *Rigidity in Curriculum*: AI-powered platforms frequently follow established learning paths that are based on past data and algorithms. This rigidity can be troublesome when there are abrupt changes in the curriculum, such as the introduction of new topics, changes in teaching methods, or altering educational priorities. AI may not react quickly to these changes, resulting in a mismatch between the platform's content and the changing academic scene.

6. Ethical Considerations: Ensuring Transparency and Equity

AI in education raises ethical concerns regarding data privacy, security, and algorithmic biases. Safeguarding student information, ensuring transparent data usage, and mitigating biases are critical considerations when implementing AI systems. Ethical concerns about AI have also emerged, with conversion centered on the racial bias (Marwala, 2023), privacy, accountability, and the impact on jobs and society. Efforts are being made to ensure ethical AI development and governance. AI continues to evolve as technology progresses, pushing the limits of what machines can accomplish. The future of AI has enormous promise, with continuous research and investigation in areas such as explainable AI, quantum computing, and social intelligence, as well as efforts to develop computers with human-level intelligence across a wide range of tasks. AI is a dynamic and fast-expanding field with the potential to transform industries, enhance efficiency, and have a wide-ranging impact on our lives. However, As we embrace the potential of AI in mathematics education, it is crucial to address ethical considerations and promote transparency and equity:

1. *Data Privacy and Security*: The collection and analysis of student data require strict adherence to privacy and security protocols. Educational institutions and AI developers must prioritize protecting student information, ensuring that data is handled securely and used only for educational purposes. Establishing strong measures and regulations to protect student's personal information from illegal access must be upheld (Elliott & Soifer, 2022; Li & Zhang, 2017).

2. *Algorithmic Bias and Fairness*: AI algorithms are only as unbiased as the data on which they are trained. Care must be taken to mitigate biases and ensure fairness in algorithmic decision-making. Regular audits, diverse datasets, and ongoing monitoring are essential to minimize the risk of perpetuating biases in AI systems (Mollick & Mollick, 2022).

3. *Inclusive Access and Digital Divide*: Addressing the digital divide is crucial to ensure equitable access to AI-powered mathematics education. Efforts should be made to provide students from all socioeconomic backgrounds access to AI technologies, thus reducing disparities and promoting inclusivity.

4. *Collaboration*: To navigate the complexities of AI in mathematics education effectively, collaboration among educators, researchers, policymakers, and AI developers is essential. This collaboration can lead to the development of ethical guidelines, best practices, and evidence-based strategies for integrating AI to maximize benefits while mitigating risks.

5. *Public Engagement and Participation*: Involving the public in discussions about AI deployment in areas like mathematics education that impact society ensures ethical AI development and responsible decision-making and builds trust and confidence in the public. We may cooperatively work for technologies that benefit society, uphold ethical norms, and address the concerns and ambitions of many populations by involving the public in conversations regarding AI deployment. Public participation fosters a sense of ownership (Popescu, 2022) and responsibility in defining future of AI.

7. Recommendations

Educators can integrate AI into mathematics education while mitigating risks effectively by following practical strategies or recommendations.

To effectively integrate AI into mathematics education, educators should first priortieze fostering computational thinking skills among students. This involves teaching them how to break down problems into smaller, more manageable parts and use algorithms to solve them, aligning with foundational principles of AI. Also, educators should continuously assess and monitor AI technologies to ensure they align with pedagogical goals and are free from biases. Educators should actively engage students in hands-on activities and projects that involve AI, allowing them to explore and experiment with the technology. This can be done through coding exercises, simulations, and real-world applications that demonstrate the practical use of AI in solving mathematical problems. By providing students with opportunities to interact with AI tools and algorithms, educators can help them better understand how AI works and its potential to enhance their mathematical abilities. In addition, educators should promote a growth mindset among students, encouraging them to improve AI as a tool to assist them in their learning journey rather than viewing it as a replacement for their problem-solving skills. By instilling a positive attitude towards AI, educators can create a supportive and inclusive learning environment where students feel empowered to explore and utilize AI in their mathematical pursuits.

Subsequently, educators must equip themselves with the necessary knowledge and skills to effectively integrate AI into mathematics education. This may involve professional development opportunities, such as workshops, courses, or online resources, where educators can learn about the latest advancements in AI technology and how to integrate them into their mathematics teaching practices. Furthermore, by staying informed and up-to-date, educators can confidently incorporate AI tools and methodologies into their mathematics curriculum. By doing so, mathematics teachers can enhance student learning experiences and provide them with valuable skills that are increasingly relevant in today's digital world. While integrating AI into mathematics education, students can develop critical thinking, problem-solving, and analytical skills essential for success in the 21st-century workplace. As AI continues to advance and become more prevalent in society, other stakeholders such as policymakers, parents, industry professional and mathematics teachers must embrace this technology and prepare students for the future. Also, by leveraging AI in mathematics education, teachers can create engaging and personalized learning experiences that cater to each student's individual needs and abilities. Ultimately, integrating AI into mathematics education has the capacity to revolutionize the way students learn and engage with mathematical concepts, making learning more adaptive, interesting, interactive, and impactful.

8. Limitations

The study focuses on the good, bad, and ugly aspects of AI in mathematics education; it is based on a qualitative conceptual review and uses secondary data for its analysis. For example, incorporating quantitative data analysis alongside qualitative methods could provide a more robust understanding of the impact of AI in education. The study was limited to mathematics education, but future research could explore the applications of AI in other subject areas as well. The study is also restricted to the autoethnography research method, which might introduce biases. It could be noteworthy for future studies to consider combining other forms of research methodology for a comprehensive view.

9. Conclusion

By harnessing the good, addressing the challenges, and mitigating the potential drawbacks, we can leverage AI effectively to enhance mathematics education and empower students with the necessary skills for the future. AI has the potential to revolutionize mathematics education, offering personalized learning experiences, adaptive assessments, and interactive environments. However, it is crucial to approach AI integration thoughtfully, considering the potential drawbacks and ethical considerations. By promoting transparency, ensuring equity, and fostering collaboration, we can harness the benefits of AI while preserving the essential human elements that contribute to effective mathematics education. Doing so can create a future where AI and human educators work together to empower students with the mathematical skills, critical thinking abilities, and ethical awareness necessary for success in an ever-evolving world.

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