Towards the Use of Generative AI in Education

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Abstract*—This summary refers to a full research article. The article presents a Systematic Literature Review (SLR) on Generative AI (GenAI), encompassing key concepts, algorithms, applications, challenges, and trends related to education. The aim is to provide a comprehensive overview of the current state of GenAI, identifying future research directions in this evolving field. Following Kitchenham's SLR protocol, a search string ("Generative AI" AND "Generative") was planned for use in the search fields of four highly relevant academic data repositories: Institute of Electrical and Electronic Engineers (IEEE), Scopus, Association for Computing Machinery (ACM), and Science Direct. The search covered the period from 2018 to 2023, resulting in 271 selected articles. After applying inclusion criteria, 21 articles were analyzed in the final review phase. GenAI has emerged as a fascinating and promising research area, seeking to empower computational systems to create original content such as images, music, text, and even human interactions. By combining advanced algorithms, machine learning, and neural networks, it stands out for its unique ability to generate creative and realistic results, surpassing conventional human capabilities. It remains a dynamically evolving field, with new techniques and approaches continuously emerging. In exploring the application of GenAI in education, ethical considerations, such as student data privacy and equitable access to advanced educational technologies are vital. Ensuring adequate data protection and avoiding the amplification of existing biases are critical aspects when implementing GenAI solutions in schools and educational institutions. Key findings emphasize the importance of addressing educational disparities, investing in network infrastructure and computational resources, promoting equity in data collection and generative model training. Additionally, international collaboration and knowledge sharing play a crucial role in ensuring the widespread accessibility and utilization of GenAI benefits in diverse educational and geographic contexts. In conclusion, the application of GenAI in the educational context necessitates a careful, ethical, and participatory approach. Addressing ethical challenges, promoting equity, actively involving educators and students, and striving for positive educational impacts are fundamental elements for the responsible and effectiveimplementation of GenAI in education. Ongoing research and collaboration among academia, education professionals, and decision-makers are essential to enhance this field and fully leverage the benefits of GenAI in the educational landscape.

***Index Terms*—Generative AI, Education, Ethical Challenges, Equity.**

I. INTRODUCTION

In education, Artificial Intelligence (AI) represents a transformation in the teaching and learning process. By personalizing learning, AI promotes more effective and engaging educational environments. Teachers and students benefit from the automation of routine tasks, allowing for greater dedication to creative and critical activities.

The evolution of Generative Artificial Intelligence (GenAI) is propelled by innovative techniques that enable significant advancements in generating realistic and diverse content. Since the introduction of Generative Adversarial Networks (GANs) by [1], these techniques have revolutionized AI's ability to create and generate new samples across various domains.

In addition to GANs, other techniques have contributed to the evolution of GenAI. Variational Autoencoders (VAEs), introduced by [2], combine variational inference and neural networks to learn a latent representation of data and generate new samples based on this representation. Normalizing Flows, such as Real-Valued Non-Volume Preserving (Real NVP) and Generative Flow with Invertible 1x1 Convolutions (Glow), are generative models that use continuous and differentiable transformations to model complex distributions.

Other approaches include attention-based generative networks, such as the Transformer proposed by [3], widely applied in text generation and automatic translation, and recurrent generative networks, such as Long Short Term Memory (LSTMs), used for generating temporal sequences, such as music and audio.

These techniques drive the GenAI's capability to create realistic and diverse content across various domains, such as images, text, music, and more. However, it's important to note that the field of GenAI remains in constant evolution, with new techniques and approaches emerging continuously.

Nevertheless, when exploring the application of GenAI in the educational context, it's paramount to consider ethical issues, such as students' data privacy and equity in access to advanced educational technologies. Ensuring adequate data protection and avoiding the amplification of existing biases are key aspects that must be carefully addressed when implementing GenAI-based solutions in schools and educational institutions.

In this article, we will present an SR of the literature on generative AI, covering the main concepts, algorithms, applications, challenges and trends related to education, with the aim of providing a comprehensive overview of the current state of generative AI, as well as identifying future directions research, ethical challenges, best practices and educational impacts that guide development in this constantly evolving field.

II. Theoretical foundation

A. Fundamental concepts of Generative AI

GenAI is a type of AI that utilizes machine learning models to generate new data, such as images, music, or text, instead of solely analyzing and categorizing existing data. This is achieved by training models on large datasets (LLMs), enabling the model to generate new data based on this training [4].

The evolution of GenAI has been driven by various innovative techniques and approaches over time. Here are some of the key techniques that have contributed to the evolution of GenAI:

1. **Generative Adversarial Networks (GANs)**: GANs, proposed by [1], are a fundamental approach for generating realistic content. This technique involves the simultaneous training of two neural networks, a generator and a discriminator, which compete against each other. The generator network aims to produce samples that deceive the discriminator network, while the discriminator network aims to distinguish between real and generated samples. This competition results in an iterative learning process that leads to the generation of increasingly authentic and high-quality samples.

2. **Variational Autoencoders (VAEs)**: VAEs, introduced by [2], are generative models that combine variational inference techniques and neural networks. They enable learning a latent representation of the data and generating new samples based on this representation. VAEs are widely used for generating images, text, and audio.

3. **Normalizing Flows**: Normalizing Flows, such as Real NVP [5] and Glow [6], are a class of generative models based on continuous and differentiable transformations. These transformations are applied to a simple base distribution, such as a Gaussian distribution, to model distributions of high complexity. Normalizing Flows have been successfully applied in image generation and other content generation tasks.

4. **Attention-based Generative Networks**: Attention-based generative networks, such as the Transformer [3], have been widely used in text generation and automatic translation. These models employ attention mechanisms to capture semantic and syntactic relationships in text sequences, enabling the generation of fluent and coherent translations.

5. **Recurrent Generative Networks (RGN)**: RGN, such as LSTMs [7], are used for generating temporal sequences, such as music and audio. These networks can model temporal dependencies and generate sequences with structure and coherence.

These techniques have played a fundamental role in the evolution of GenAI, enabling the generation of realistic, diverse, and high-quality content across different domains. However, it's worth noting that the field of GenAI continues to evolve, with new techniques and approaches being explored to further enhance machines' content generation capabilities.

B. Popular Generative AI Algorithms and Techniques

The field of GenAI has been propelled by a variety of algorithms and techniques that enable the creation of new and authentic content. These algorithms and techniques have played a significant role in the GenAI's ability to generate realistic samples across various domains, such as images, music, text, and more. In this topic, we will explore some of the popular algorithms and techniques that have driven the evolution of GenAI.

1. **Image Generation**: GANs have been widely used in generating realistic images across various domains, such as human portraits, landscapes, and artwork [8]. These techniques enable the synthesis of increasingly authentic and high-quality samples.

2. **Text Generation**: Natural language-based models, such as VAEs and GANs, have been applied in generating fluent and coherent text [3]. These models are capable of generating automatic translations, text summaries, and even stories and poetry.

3. **Music and Audio**: GenAI has been applied in generating original musical compositions, such as DeepBach proposed by [9]. Additionally, VAEs have been applied in audio and voice synthesis, enabling the generation of realistic sounds and voices [10].

In addition to the domains mentioned earlier, GenAI has also been applied in other contexts, such as: Video Generation, Art and Design, Code and Programming, Games and Virtual Environments, and Dialogue and Conversation Generation.

C. Large Language Models

Large Language Models (LLMs) are AI systems designed to understand and produce text on a massive scale. These models have been driven by significant advancements in neural network architecture. In particular, the Transformer, proposed by [3], is a fundamental architecture in this advancement. LLMs are trained on large datasets of textual data using supervised learning techniques and transfer learning using pre-training. This approach, described in [11], enables the models to learn linguistic patterns and complex contexts.

Once trained, LLMs demonstrate the ability to generate coherent and relevant text in response to specific inputs, opening doors to a wide range of applications in automatic translation, assisted text generation, and other linguistic tasks. In recent years, LLMs have made significant advancements in the field of Natural Language Processing (NLP) to generate human-like text, answer questions, and perform other language-related tasks with high precision.

An exemplary instance of these models is the Chat Generative Pre-trained Transformer (ChatGPT), which incorporates three key concepts: generative, pre-trained, and transformer. With an architecture based on the Transformer, this pre-trained model can produce content using LLMs. ChatGPT, in particular, is recognized for its ability to interact in chat environments, simulating nearly real conversations between humans.

To understand GPT technology, it's significant to elucidate the concept of Pre-trained Language Models (PLMs), which are machine learning models subjected to training for a specific task using a vast corpus of text. Initially, the PLM undergoes large-scale training on an extensive dataset, and subsequently, it is fine-tuned for a specific task. During this initial training process, the model develops an understanding of the statistical patterns present in the provided text sets, encompassing word co-occurrence, sentence structures, and grammar. Then, in the fine-tuning stage, the PLM learns to effectively apply the acquired knowledge to perform a specific task.

D. Challenges and Limitations of Generative AI

While GenAI has made significant advancements, it still faces challenges and limitations that need to be addressed. Below are some of the main challenges and limitations identified:

1. **Ethical Issues and Algorithmic Bias:** GenAI can reproduce and amplify biases present in training datasets, leading to undesirable and potentially discriminatory outcomes [12]. It is essential to address these ethical issues and ensure fairness in content generation through careful data selection and model training.

2. **Interpretability and Transparency of Generative Models**: Generative models, such as GANs and VAEs, can be highly complex and difficult to interpret. The lack of transparency regarding the content generation process can limit trust and adoption of these models in critical environments, such as healthcare [13]. It is vital to develop approaches that enable understanding and interpretation of how these models operate.

3. **Scarcity and Quality of Training Datasets**: Generating high-quality samples requires adequate and representative training datasets. However, in some domains, it can be challenging to obtain large and diverse enough datasets to train robust generative models [14]. Additionally, the quality and consistency of training data can directly affect the quality of generated samples.

4. **Computational Limitations and Resource Requirements**: Generative models, especially those with complex architectures, may require significant computational power and storage resources for training and inference. Additionally, generating high-quality samples may require considerable processing time, which can be a practical limitation in certain scenarios [15]. It is important to consider these computational requirements when developing and deploying generative models.

It is crucial to address these limitations to ensure equitable and inclusive adoption of GenAI worldwide, promoting equal access to the benefits that this technology can offer. Considering the educational bias, it is important to highlight the following challenges:

5. **Access to Computational Resources and Network Infrastructure**: Generating advanced generative models requires significant computational resources, such as processing power and storage capacity. Developing countries or regions with limited network infrastructure may face challenges in accessing these resources, which can affect their ability to fully explore and utilize GenAI.

6. **Educational and Skills Disparities**: The skills required to develop and utilize GenAI are highly specialized and demand advanced knowledge in computer science and machine learning. Educational disparities between first-world and third-world countries may lead to inequalities in the ability to harness the benefits of GenAI, both in terms of research and practical application.

7. **Disparities in Access to Data and Quality of Training Sets**: GenAI relies on representative and high-quality training datasets. Countries with limited resources may face challenges in collecting and accessing large datasets, which can limit their ability to train robust generative models and produce high-quality results.

8. **Algorithmic Bias and Equity of Conditions**: Generative models can reflect and amplify biases present in training datasets, which can lead to discriminatory or unfair outcomes. Special care is needed to ensure that generative models are trained on balanced and representative data, taking into account cultural, social, and educational differences between first-world and third-world countries.

9. **Knowledge Transfer and International Collaboration**: International collaboration and knowledge transfer play an important role in advancing GenAI. Third-world countries may face challenges in actively participating in research networks and international collaboration, which can limit their access to resources, knowledge, and recent advancements in the field.

These challenges and limitations underscore the importance of addressing educational disparities, investing in network infrastructure and computational resources, and promoting equity in data collection and generative model training. International collaboration and knowledge sharing also play a pivotal role in ensuring that the benefits of GenAI are widely accessible and leveraged in different educational and geographical contexts.

In addition to the difficulties and challenges presented, it is necessary to highlight the significant impacts described by [16] on Computer Science (CS) education and the role of Software Engineers.

1. **Technological Evolution**: The rapid change in programming languages, frameworks, and APIs over the years requires constant updates in CS educational curricula to keep pace. This includes transitioning from a "Mobile First" focus to an "AI First" approach, as observed at Google.

2. **CS Education**: The importance of specializations in CS for undergraduate students is evident due to the rapid evolution of the field. CS undergraduate programs are adapting to the use of GenAI both as a productivity tool and pedagogical aid, offering real-time feedback and assisting students in overcoming "programmer's block." There is also a need to elevate the level of abstraction for software engineers in the industry, given the productivity assistance provided by AI.

3. **Role of Software Engineer**: The introduction of LLMs is transforming the activities of software engineers, especially in code generation and designing systems based on detailed prompts. GenAI is changing the role of the software engineer, providing assistance in code and system design.

4. **Curriculum Update**: The need for CS educators to adjust curricula to prepare students for the future of automated software engineering is evident. This includes incorporating tools and concepts of GenAI to ensure students are equipped with the necessary skills to tackle future challenges.

5. **Challenges and Opportunities**: While educators acknowledge the risks of over-reliance and academic integrity associated with the use of GenAI, they also see opportunities to enhance teaching with these tools. It is essential to strengthen knowledge sharing between industry and academia to prepare students for the future of automated software engineering.

E. Applications of Generative AI in Education

With the advancement of GenAI technologies, new opportunities arise to enhance teaching and learning, offering personalized, interactive, and adaptive solutions. Below are some applications:

1. **Learning Personalization**: AI-based systems offer opportunities to personalize learning, adapting educational content according to the individual needs of each student [17].

2. **Virtual Tutors**: AI agents can play the role of virtual tutors, providing individualized support to students, answering questions, explaining complex concepts, and conducting real-time tutoring sessions [18].

3. **Creation of Educational Content**: AI can be employed in the automated creation of educational materials, including textbooks, slide presentations, and educational videos, streamlining the process of producing high-quality educational resources [19].

4. **Automated Assessment**: AI algorithms are capable of automatically assessing students' work, providing immediate feedback and enabling continuous and personalized assessment of student progress [20].

5. **Simulations and Virtual Learning Environments**: AI can be used to create simulations and virtual learning environments, offering students practical and immersive experiences in various fields of study [21].

6. **Automatic Translation of Educational Content**: AI systems can facilitate the automatic translation of educational content into different languages, promoting accessibility and internationalization of education.

These applications demonstrate the potential of AI to enhance the effectiveness and efficiency of the educational process, offering innovative solutions to the challenges faced by educators and students in the digital age. However, effectively integrating AI into the educational environment requires a series of social and structural transformations. As AI establishes itself as a powerful tool to enhance learning and teaching, it is essential to recognize the comprehensive and multifaceted implications of this advancement. This integration process goes beyond the adoption of new technologies and encompasses a profound review of curricula, pedagogical practices, technological infrastructure, and educational policies. In this perspective, it is essential to carefully explore the critical considerations that permeate this transformation, highlighting both the challenges and opportunities that arise with the application of AI in education.

For effective use, several societal changes are needed, and some important considerations require highlighting:

1. **Update of Educational Curriculum**: It is essential for educational curricula to be updated to include AI literacy from the early stages of education. This involves introducing basic AI concepts, such as machine learning algorithms and AI ethics, to prepare students for an increasingly technological world.

2. **Teacher Training**: Teachers need to receive adequate training on how to effectively integrate AI into their pedagogical practices. This includes understanding how to utilize AI-based tools to personalize learning, support students, and assess their progress more efficiently.

3. **Equitable Access to Technology**: To ensure that all students benefit from the use of AI in education, it is essential to ensure equitable access to technology. This requires investments in technology infrastructure in schools and ensuring that all students have access to appropriate devices and connectivity.

4. **Data Management and Privacy**: With the use of AI in collecting and analyzing student data, it is vital to implement robust data protection and privacy policies. This includes ensuring the security of student data, obtaining appropriate consent, and ensuring transparency about how the data is being used.

5. **Development of Social and Creative Skills**: Despite the significant support offered by AI in education, it is important to recognize that there are certain skills, such as critical thinking, creativity, and social skills, that cannot be replaced by technology. Therefore, it is necessary to ensure that students also develop these essential skills for success in the digital world.

These societal changes are essential to ensure that the use of AI in education is effective, ethical, and inclusive, enabling all students to benefit from the opportunities offered by technology.

III. Literature Review

According to [22], Systematic Review (SR) is a method used to conduct bibliographic reviews in an organized manner, with well-defined stages, providing greater scientific grounding and credibility. It is a structured process involving the search, selection, and critical analysis of relevant studies, with the aim of answering one or more research questions. The basic steps of an SR include:

1. **Formulation of research questions**: Defining the questions that will be answered by the SR, related to the objective, variables of interest, and the scope of the research;

2. **Search strategy**: Develop a comprehensive and systematic search strategy to identify all relevant studies on the topic. This strategy may involve keywords, boolean operators, and specific filters, and should be applied to digital databases, journals, conferences, repositories, and other relevant sources;

3. **Study selection**: Conduct an initial screening based on pre-defined inclusion and exclusion criteria. Evaluate the titles, keywords, and abstracts of the studies identified in the previous stage to identify those that meet the selection criteria;

4. **Data extraction**: Extract and record relevant information from the selected studies in a standardized format. This includes details about the study design, sample characteristics, key findings, and conclusions;

5. **Interpretation of results**: Interpret the results obtained in relation to the research questions. Identify gaps in the evidence, inconsistencies in the results, and possible trends in the included studies.

A. Definition of Research Questions

Four research questions (RQs) were defined in order to search for evidence that meets the objective proposed in this article:

RQ1: What are the main ethical challenges associated with the implementation of GenAI in the educational context and how can they be mitigated?

RQ2: What are the best practices for promoting equity in access to advanced educational technologies based on GenAI, considering the existing disparities between regions and educational institutions?

RQ3: How to engage educators and students in the decision-making process and development of solutions based on GenAI, ensuring a participatory and inclusive approach?

RQ4: What are the impacts of GenAI on education and how can it be applied to improve the educational experience and the creation of teaching materials?

These research questions guide the SR, providing a framework to identify and analyze existing studies, as well as contribute to the overall understanding.

B. Conducting Research and Data Extraction

[22] defines the need to construct an appropriate strategy in order to narrow down the research scope. For this purpose, the search string ”Generative AI” AND ”Generative” was used in the internationally recognized digital libraries in the computing field, as listed below: IEEE Xplore Digital Library[1], Scopus[2], Association for Computing Machinery (ACM)[3], Science Direct[4]. Another relevant definition, according to [22], is the choice of inclusion criteria, which aim to identify and select key documents providing content directly related to the research questions. To guide the study selection process, the following exclusion criteria were defined:

- Articles not accessible in full;
- Summarized articles, tutorials, workshop reports;
- Secondary and tertiary studies;
- Duplicate studies: only the most recent was included;
- Articles expressing personal viewpoints or expert opinions;
- Articles that do not address GenAI, or where this functionality is not the focus, or at least a highlighted part, of the selected studies; and
- Studies that address GenAI only as future work.

If the study did not meet at least one of the criteria listed above, it would be excluded from the process. The search was divided into three stages, as presented in the Table I.

- Stage 1: Applying the search string to each repository, collecting the results found;
- Stage 2: Using the inclusion and exclusion criteria to refine the results from Stage 1;
- Stage 3: Reading and classifying the results from Stage 2, considering the content about GenAI.

TABLE I
OVERALL SEARCH RESULT IN REPOSITORIES

Search Sources	Stage 1	Stage 2	Stage 3:
IEEE	13	6	4
SCIENCE DIRECT	116	19	11
SCOPUS	116	10	6
ACM	26	4	0
result	271	39	21

Source: Author.

The results of stage 3 are listed in Table II, according to the related repositories.

TABLE II
SELECTED STUDIES

Repository	Article
IEEE	[4], [23], [24], [25],
Scopus	[26] [27] [28], [29], [30], [31],
Science Direct	[32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42],

Source: Author.

IV. RESULTS AND DISCUSSION

Grouped by research questions, results and discussions will be presented.

RQ1: What are the main ethical challenges associated with the implementation of GenAI in the educational context and

[1]www.ieeexplore.ieee.org
[2]www.scopus.com
[3]www.dl.acm.org
[4]www.sciencedirect.com

how can they be mitigated? The implementation of GenAI in the educational context brings along a series of ethical challenges that must be considered and addressed appropriately. The article [38] introduces a concern about students' privacy, as the model could be used to collect sensitive information without the knowledge or prior consent of the students. There are also concerns about the potential for discrimination against certain students if the model is not trained on data that is representative of all students. [23] highlights the importance of considering the ethics of using GenAI technology in education and ensuring that it is used in a responsible and transparent manner. As a proposed solution, [38] suggests adequate monitoring and regulation, protection of students' privacy, transparency and accountability, and education and awareness about the use of such technologies.

RQ2: What are the best practices for promoting equity in access to advanced educational technologies based on GenAI, considering the existing disparities between regions and educational institutions? [26] discusses the need to ensure equity and inclusion in personalized learning and suggests the necessity of developing critical skills to assess and use information generated by AI. [43] highlights that fairness is a central issue in discussions about the increasing influence of AI in education and that the use of AI can lead to problematic or harmful outcomes for certain populations if bias and ethical issues are not addressed. Additionally, the article mentions that creating large open datasets to develop, train, And validate AI models will be essential to address equity issues in education and suggests solutions such as the need to develop AI literacy and skills for educational stakeholders. Moreover, the article emphasizes the importance of developing policies that enhance the responsiveness of educational systems to rapid changes driven by AI.

RQ3: How to engage educators and students in the decision-making process and development of solutions based on GenAI, ensuring a participatory and inclusive approach? [37] highlights that the lack of knowledge and skills in AI among educators is one of the main challenges in implementing AI literacy in education. To engage educators, the article suggests that universities provide professional training in AI for teachers and that appropriate AI activities and curricula be developed for different age groups. Additionally, it emphasizes the importance of ensuring that educators have access to adequate resources and tools to implement AI literacy in their classrooms. Educators should also be encouraged to participate in discussions and forums on AI and to share experiences and best practices. [43] emphasizes the importance of involving educators in the design process of AI systems for education to ensure that these systems meet the needs of students and teachers and are appropriately designed. The text underscores the importance of involving educators in discussions about ethical and privacy issues related to the use of AI in education. Reinforcing these concepts, another way to engage educators is to provide opportunities for them to learn about GenAI and discuss its potential uses and ethical and pedagogical challenges. This can include workshops, training sessions, and discussion forums. Additionally, educators can be encouraged to experiment with the use of GenAI tools in their own teaching practices and to share their experiences and reflections with other educators.

RQ4: What are the impacts of GenAI on education and how can it be applied to improve the educational experience and the creation of teaching materials? The article by [26] discusses how AI has significant impacts on education and society as a whole. Some of the positive impacts include personalized learning, improved efficiency and accessibility of education, and the creation of new learning opportunities. However, the article also highlights the ethical and pedagogical challenges associated with AI use in education, including the lack of transparency regarding algorithms used in AI systems, the need to develop critical skills to assess and use information generated by AI, and the broader societal impacts of AI, including job automation, privacy and data security, and the concentration of power in technology companies. In the same vein, [44] mentions that AI can help reduce barriers to a better quality of life, such as the racial gap in reading proficiency. However, the text also highlights that AI has limitations, such as the need for adequate data and training techniques, and that AI cannot replace human skills such as creativity and empathy. The article also mentions that companies are eager to use AI for profit-making purposes. In summary, the impact of AI can be either positive or negative, depending on how it is used and implemented.

V. Conclusion

In summary, the literature review on the implementation of GenAI in the educational context provided a comprehensive insight into the challenges, best practices, and impacts of this technology. The results obtained regarding research questions QP1 to QP4 provided valuable insights to guide future research and actions in the field of GenAI in education.

Addressing **RQ1**, we identified that the main ethical challenges associated with the implementation of GenAI in the educational context are related to student data privacy, equity in access to technology, algorithmic bias and fairness, transparency and explainability of models, as well as the need for accountability and human oversight. To mitigate these challenges, it is essential to adopt data protection measures, promote digital inclusion, ensure representativeness in training data sets, seek transparency of models, and ensure responsible and informed supervision.

Regarding **RQ2**, we highlighted that the best practices to promote equity in access to advanced educational technologies based on GenAI should consider existing disparities between regions and educational institutions. This includes the development of policies and initiatives that ensure adequate resources, provision of training and support to educators, and seeking collaborative partnerships to overcome technological barriers and promote equal educational opportunities.

RQ3 emphasized the importance of involving educators and students in the decision-making process and development of solutions based on GenAI. This implies adopting a participatory and inclusive approach, listening to their perspectives, needs, and concerns. Co-creating solutions and promoting a culture of collaboration among educators, students, and researchers can contribute to the responsible and effective implementation of GenAI in education.

Finally, **RQ4** highlighted the impacts of GenAI on education and its potential to improve the educational experience and the creation of educational materials. GenAI can offer advanced resources for personalized teaching, creation of interactive and adaptive content, as well as support for the development of innovative educational materials. However, it is essential to consider ethics and the educational context when applying this technology, always seeking sustainable educational benefits aligned with the needs of students and educators.

Thus, based on the results obtained, it can be concluded that the implementation of GenAI in the educational context requires a careful, ethical, and participatory approach. Considering ethical challenges, promoting equity, active participation of educators and students, and seeking positive educational impacts are crucial elements for the responsible and effective implementation of GenAI in education. Research and ongoing collaboration between academia, education professionals, and decision-makers are essential to enhance this area and fully harness the benefits of GenAI in the educational landscape.

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