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Harnessing Generative AI for Personalized Learning: A Review in the Context of National Education Policy, 2020

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Abstract:
The inclusion of Artificial Intelligence (AI) in education has been a hot topic in recent years, with the National Education Policy (NEP) 2020 identifying the need to harness AI for improving learning outcomes. This review discusses the prospects of Generative AI (GenAI) in transforming personalized learning, in consonance with the objectives outlined by the NEP. Through an exploration of current literature, the paper analyzes how GenAI methods are being used to design personalized learning experiences. In addition, it critically examines the existing state of personalized learning systems, highlighting gaps and challenges. In a comparative approach, the review brings out the shortfalls in current strategies and proposes possibilities for further research, which bridges these shortcomings to achieve more efficient and scalable personalized learning solutions.
***Keywords**: Artificial Intelligence (AI), National Education Policy (NEP), Generative AI(GenAI), Machine Learning (ML), Deep Learning (DL).*

Introduction
Context and Background:
The origin of Artificial Intelligence (AI) can be traced back to 1956 Darmouth Conference organized by John McCarthy (Adrian, 2019). This event initiated the beginning of AI as a distinct discipline. The early years of AI saw a considerable progress in problem-solving, learning and knowledge representation. (Buchanan, 2005). The two '*AI winters*' witnessed in the decade of 1970's and 1990's slowed down the pace at which AI was growing. This was a time which witnessed a decrease in the funding for research in AI. Nevertheless, some significant factors led to the resurgence of AI. To start with, in the late 1980's and early 1990's major Machine Learning (ML) techniques like Decision Trees, Support Vector Machines, Adaboost, and Random Forests emerged. Adding to it, Neural networks gained traction after the 1986 back-propagation breakthrough. This laid a foundation for AI's revival. Additionally, the availability of high-quality, real-world datasets fuelled AI training, improving prediction and classification performance. Moreover, advancements in hardware, including AI chips and neural processing units (NPUs), significantly accelerated AI training and execution. Lastly, the landmark AI achievements, such as IBM's Watson winning *Jeopardy!* in 2011 and AlphaGo defeating top Go players, demonstrated AI's capabilities. AlphaGo Zero, trained purely through Reinforcement Learning, further showcased AI's rapid self-improvement. (Jiang, Li, Hao Luo, Shen Yin, & Okyay Kaynak, 2022).
The Rise of Generative Artificial Intelligence (GenAI)
The introduction of the Transformer architecture in the seminal paper "Attention Is All You Need" (Vaswani & Noam, 2017) marked a transformative moment in artificial intelligence, fundamentally reshaping the way machines process and generate human-like content. By leveraging self-attention mechanisms and parallel processing capabilities, Transformers significantly improved the efficiency and scalability of AI models, replacing traditional

sequential architectures like recurrent neural networks (RNNs). This innovation laid the foundation for state-of-the-art Generative AI (GenAI) models, which have since become instrumental in various applications.
Generative AI represents a subset of artificial intelligence focused on the autonomous creation of novel content across multiple modalities, including text, images, audio, video, and code. Figure-1 describes the position of GenAI in the realm of Artificial Intelligence (Lytras, 2023).

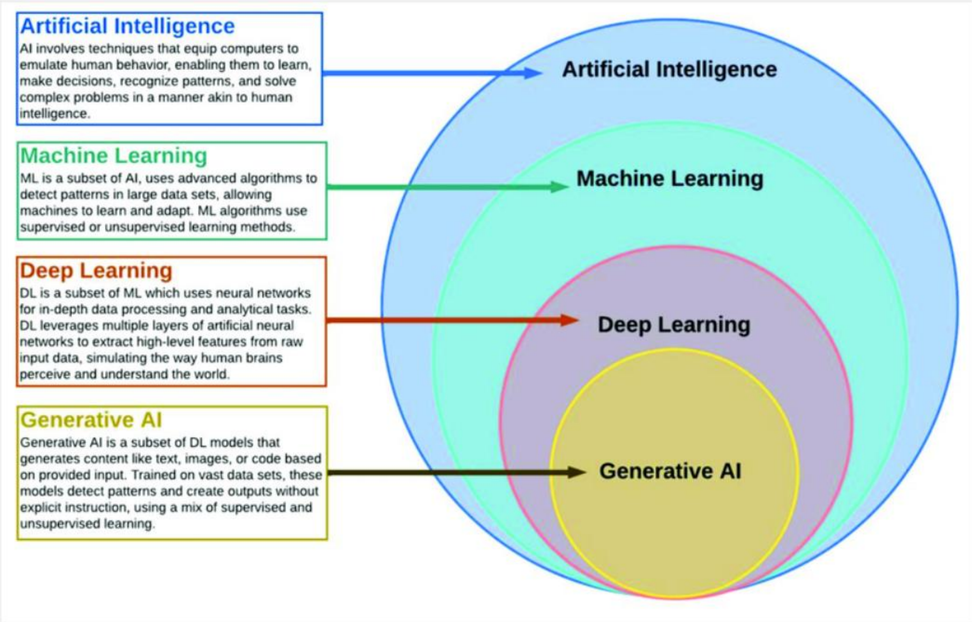

Figure 1: The position of Generative AI in the realm of AI (File:Unraveling AI Complexity - A Comparative View of AI, Machine Learning, Deep Learning, and Generative AI.jpg - Wikimedia Commons)

Unlike traditional AI systems, which are primarily designed for classification, prediction, or decision-making based on pre-existing data, GenAI models learn patterns from vast datasets and generate new, contextually relevant outputs in response to a given prompt. This ability to create human-like content distinguishes GenAI from other branches of AI, making it a foundational technology in creative automation, content generation, and data augmentation**.** The adaptability of GenAI has led to its widespread adoption across industries ranging from healthcare, financial services to software development and education (Osman ŞAHİN, 2024).
As mentioned above, GenAI models are trained on vast datasets through which they learn and can generate contextually relevant outputs. However, here is where the issue of 'bias' in GenAI model arises. Bias can occur if a model is trained on a dataset which has imbalanced representations of certain groups. The model will likely learn and replicate these biases in the content which it generates. This matter is also highlighted in (Zhou, 2024). In this paper, the author analysed images generated by popular AI tools—Midjourney, Stable Diffusion, and DALL·E 2—to investigate potential biases. The findings revealed systematic gender and racial biases, with women and African Americans being underrepresented.

National Education Policy (NEP), 2020

The Government of India launched the National Education Policy (NEP) 2020 with a vision to transform from rote learning to conceptual learning, making education flexible, inclusive, and student centric. The policy acknowledges the necessity of equipping learners with critical thinking, creativity, and multidisciplinary knowledge to be able to adapt to a fast-changing global environment. NEP 2020 focuses on some particularly important goals such as personalized learning, multilingual schooling and adaptive assessments. It promotes competency-based learning in which students can opt for their learning trajectories according to their interests and strengths. The policy also supports formative and adaptive assessment rather than the conventional high-stakes examinations to ensure that evaluation practices emphasize student progress more than memorization. To attain these lofty objectives, NEP foresees utilizing the latest technologies. GenAI can act as an enabler for meeting these objectives (MHRD, 2020).

Synergy between GenAI and NEP

Some of the objectives put forward by NEP as mentioned above can be fulfilled by leveraging the potential offered by GenAI. For instance, GenAI can generate interactive case studies and real-world scenarios that encourage students to apply concepts rather than memorize them (Bai, 2024). This induces critical thinking rather than just focussing on rote-learning. Also, GenAI can generate contextual insights on a particular topic. This makes the understanding of complex topics easier. One core objective of NEP, 2020 is Personalised Learning so that each student progresses at their own pace. GenAI can enable this through AI-driven tutoring systems. These systems can assess the student's strength, weakness, and design student-specific learning paths. Moreover, based upon the real-time feedback from the performance of a student GenAI through the adaptive learning algorithms can design assignment and quizzes that suit the learning progress of the student. GenAI is also vital in breaking the language barriers. For students in the vernacular medium, AI-powered language translation tools can automatically convert educational materials into multiple Indian languages (Reddy, 2024). As mentioned above, the potential offered by GenAI is immense. Going ahead, GenAI can also help in Real-time AI assisted translation in classrooms. This shall allow teachers to instruct students from different linguistic backgrounds seamlessly. Thus, GenAI is a weapon with powers to possibly break all barriers in education today (Alier, 2024).

Methodology

Question under Review:

How is GenAI facilitating personalised learning especially in the context of NEP, 2020?

Search Strategy:

Databases: For conducting literature review, relevant research papers, review papers, conference proceedings were sourced from reputable databases which includes Google Scholar, IEEE Xplore and Semantic Scholar. Moreover, research AI tool named as Elicit AI was used to search relevant papers from multiple sources and accumulate their respective findings. While selecting papers the major focus was on relevance of the papers to the research topic and their citations. Some of the research papers that we referred to date as back as 2005. These papers were essential for framing the history of AI. However, when it came to GenAI and its applications to education recency as a criterion was emphasized upon.

Keywords: "Adaptive Learning and National Education Policy, 2020", "Generative AI in Education", "Personalised Learning using Artificial Intelligence", "Artificial Intelligence driven tutoring systems".

Inclusion Criteria: As the research topic talks about establishing a synergy between NEP and GenAI, the criteria for selecting papers revolved around searching for papers which talked about AI in education, AI-driven adaptive learning and Personalised-education using GenAI. Some peer-reviewed journal articles dating between 2005 and 2024 were studied upon.

Exclusion Criteria: Studies which were unrelated to AI, or which did not revolve around the application of AI in education were excluded from our study.

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Screening Process:

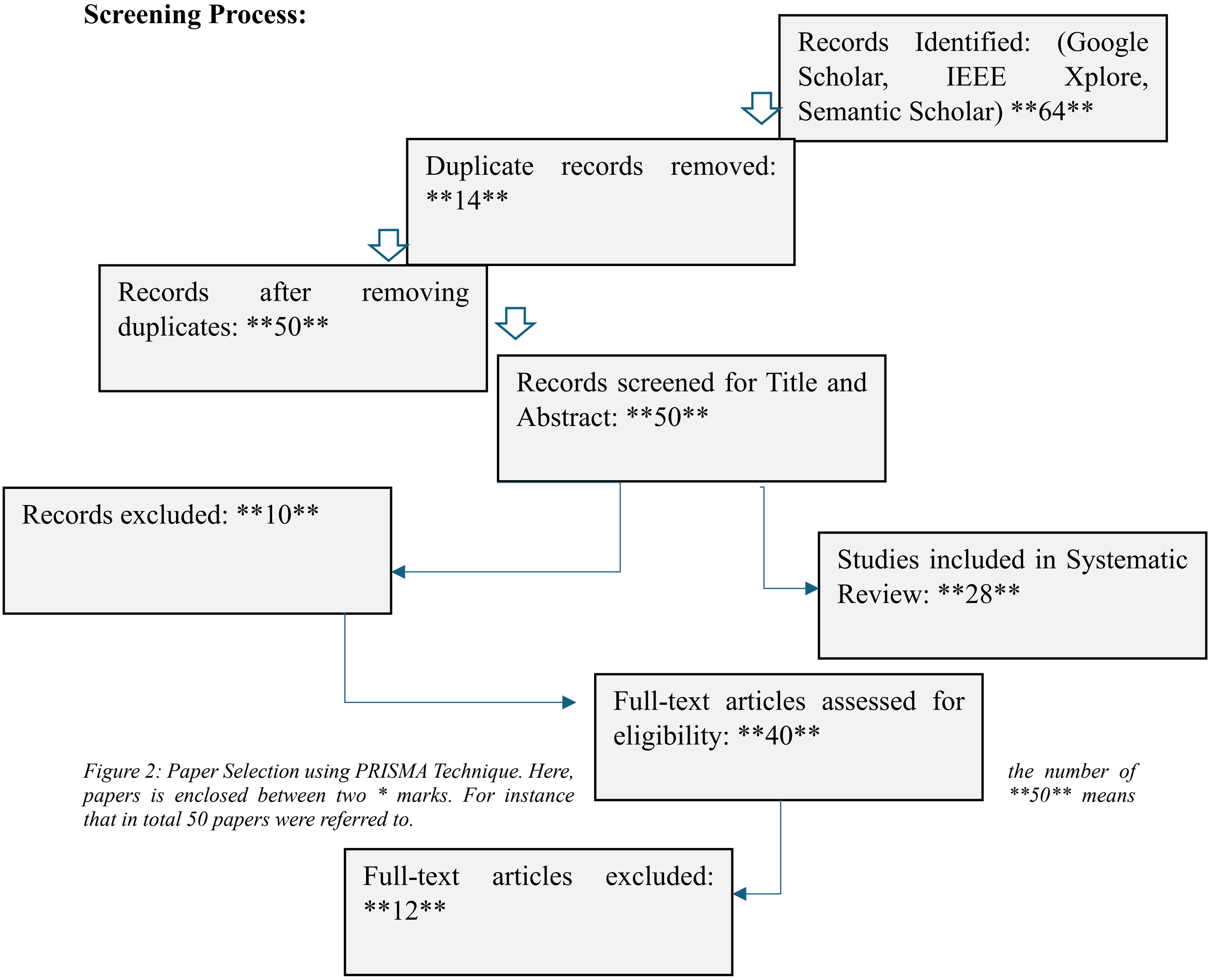

*Figure 2: Paper Selection using PRISMA Technique. Here, the number of papers is enclosed between two * marks. For instance **50** means that in total 50 papers were referred to.*

Background: GenAI in Education and its Current Development

Evolution of AI in Education:

In the past few decades, AI has contributed significantly to the field of education. The journey started from rule-based expert systems to Machine Learning (ML) - driven adaptive learning platforms and now to GenAI. Following is a brief highlight of AI's contribution to the field of education:

1. *Early AI Models*: Early AI applications in education were primarily rule-based expert systems. These systems relied on predefined logic to provide tutoring experience. For instance, the Intelligent Tutoring Systems (ITS) such as AutoTutor (Graesser, Chipman, Haynes, & Olney, 2005).This system relied on Natural Language Processing (NLP) and certain pre-programmed rules to guide students. However, the limitations of these systems were that they lacked adaptability in the sense that these systems could not learn dynamically from student interactions.
2. *The rise of ML in Education*: The rise of ML enabled personalized learning environments. For instance, IBM Watson Education, a cloud service solution helps teachers deliver truly personalized learning to improve student outcomes. With Watson Education Classroom, teachers gain the data to understand students' needs and

personalize learning activities (Gohl, 2018). Also, ML-driven platforms such as Duolingo utilize reinforcement learning to tailor content recommendations based on student progress (Bicknell, Brust, & Burr, 2023).

3. *The GenAI Revolution*: With the introduction of Transformer models, AI is now able to create personalized content, simulate virtual tutors, and generate multimodal learning materials (text, video, images, etc.). GenAI models like ChatGPT (OpenAI), Gemini (Google DeepMind) etc. have significantly enhanced student engagement.

The GenAI Breakthrough

As discussed above, transformer models have enabled AI-driven systems to understand context, generate human-like text and personalize learning experiences. One of the earliest breakthroughs was BERT (Bidirectional Encoder Representations from Transformers), developed by Google AI (Devlin, Ming-Wei, Lee, & Toutanova, 2019), which introduced context-aware language understanding. This enhanced AI-powered grading systems such as Grammarly. The introduction of OpenAI's GPT-3 and GPT-4 marked a new era in Generative AI, allowing AI to generate essays, summarize complex topics, and assist with research (Brown, 2020). These capabilities have been widely integrated into AI-powered educational tutors, such as ChatGPT, which offers step-by-step explanations, and Codex, which assists in computer science education by generating real-time code suggestions. With these breakthroughs, GenAI is playing a crucial role in personalized learning, particularly through adaptive learning platforms that dynamically analyze student progress and customize lesson plans. A prime example in this regard is Khanmigo (by Khan Academy). This platform is powered by GPT-4 (Mittal, Siva, Chamola, & Sangwan, 2024) which offers interactive tutoring and tailored explanations based on student input. This perfectly aligns with the competency-based learning approach emphasized in NEP 2020.

Personalized Learning and GenAI

GenAI and Adaptive Learning:

GenAI driven adaptive learning platforms (ALP's) are acting like a disruptive force in the field of education by offering personalised learning experiences tailored to individual students need (Dutta, et al., 2024). ALP's have demonstrated an improved learning performance as compared to traditional approach of classroom instruction. For instance, ALP's like Squirrel-AI have demonstrated that 8^{th} grade students in China using Squirrel-AI showed greater gains in a Maths test to students receiving traditional classroom learning (Wang, et al., 2020). Following table highlights major research in the field of adaptive learning and their findings:

Research Paper	Year	Total Citations	Main Findings
Performance Comparison of an AI-Based Adaptive Learning System in China (Wei, Xue, & Thai, 2018)	2018	33	This paper highlights that student performed better using the Yixue Squirrel ALP. The paper also highlights that the student data collected by ALP's helps in providing individualized feedback which thereby improves student engagement and learning efficiency.
Enhancing Educational Adaptability: A Review and Analysis of AI-Driven Adaptive Learning	2024	12	This paper explores the potential of AI-powered ALPs to personalize learning paths and impact student engagement and outcomes. The paper also compares 4 prominent ALP's Carnegie Learning, DreamBox Learning, Smart Sparrow and

Platforms (Dutta, et al., 2024)			Knewton. The paper also highlights on how ALP's can empower educators and help personalise education.
Adaptive learning and artificial intelligence in the educational space (Akavova, Temirkhanova, & Lorsanova, 2023)	2023	13	This paper states that ALPs can continuously monitor student progress and dynamically adjust the difficulty level of the content, either advancing students to more challenging material or providing additional support for struggling students. The paper also states that adaptive learning can maximize student learning potential by providing right content at the right time and in the right format.
When adaptive learning is effective learning: comparison of an adaptive learning system to teacher-led instruction (Wang, et al., 2020)	2020	113	This paper highlights the use of Squirrel AI, an ALP on Chinese 8th grade students. The study reveals that students using this ALP showed greater gains on a math test as compared to the students receiving traditional classroom teaching.
Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review (Gligorea, Cioca, & Oancea, 2023)	2023	141	This paper states that employing AI/ML algorithms have optimised personalised learning experiences by tailoring student-specific learning paths.

Table 1: GenAI for Adaptive Learning

GenAI and Language Translation:

AI has significantly advanced in real-time language translation. This advancement has transformed multi-lingual education and promoted inclusivity. The advantage of this technological progress has been that it has enabled students to translate educational content instantaneously allowing students from diverse linguistic backgrounds to access and engage with materials in their native language. Several AI-driven tools have been integrated into educational settings to facilitate real-time translation:

1. Google Translate - Utilizes neural machine translation to provide quick translations across numerous languages, supporting text, voice, and image input.
2. DeepL - Known for its exceptional accuracy, DeepL uses neural networks to translate entire documents and web pages, enhancing comprehension for student.
3. Alexa Translations: Offers specialized AI-powered solutions tailored for legal and financial education, ensuring accurate translations in professional contexts.

Following table highlights the ongoing progress in the field of language translation using GenAI:

Research Paper	Year	Citations	Major Findings
The Impact of Artificial Intelligence on	2024	21	This paper reviews the current state of AI-driven language translation systems. It also

Language Translation: A Review (Abdelgadir Mohamed, Kannan, & Bashir, 2024)			aims to provide ethical considerations in AI-driven language translation.
Evaluating the Impact of AI Tools on Language Proficiency and Intercultural Communication in Second Language Education (Fountoulakis, 2024)	2024	1	This paper highlights on how AI-driven language learning tools can enhance language proficiency. A study conducted by the authors found that 85% of teachers and 70% of students are currently using AI-supported language learning tools, indicating a significant shift towards the adoption of AI in language education.
Analysis of AI-enhanced educational tools developed in India for linguistic minorities and disabled people. (Gupta , Gupta, Bal, & Bal, 2023)	2023		This paper highlights on the initiatives undertaken by the government of India for language translation. These initiatives have especially helped the linguistic minorities and disabled people.

Table 2: GenAI for Language Translation

GenAI for Formative Assessments:

GenAI's integration into formative assessments presents a great scope of opportunities within the framework of NEP. An interesting example is a study on using GenAI in an 8-week undergraduate research methods course at a university in United States of America (Huang, Huang, & Cummings, 2024). This study highlighted that the effectiveness of ChatGPT in providing explanations and verifying students thought processes suggested that GenAI tools can play a complementary role in learning and assessment. Moreover, the study also highlighted that there is also a need to consider how GenAI tools can be integrated with traditional teaching methods to enhance the learning outcomes. The study also mentions that GenAI can be used to support flipped classroom models and as a supplementary resource for explaining complex concepts.

Following table highlights the progress made in the field of using GenAI for formative assessments:

Research Paper	Year	Citations	Major Findings
Incorporating Generative AI into Software Development Education (Petrovska, Clift, Moller, & Pearsall, 2024)	2024	15	This paper explored how GenAI can be incorporated into software development education. The study highlights that 94% of first-year students were able to generate working Java code using ChatGPT on their first attempt, and 89% felt the generated code was equal to or better than their own.

The Future of Feedback (Annika Herb, 2024)	2024	2	This paper highlights that GenAI such as ChatGPT can provide rapid, personalized feedback to students, leading to positive engagement and improved skill development. Moreover, Utilizing GenAI for feedback can aid students in planning, drafting, and revising their work.
AI and Formative Assessment: The Train Has Left the Station (Xiaoming Zhai, 2024)	2024	3	This paper highlights that AI-based formative assessment are being used for various applications such as open-ended questions, scaffolding, analogy generation, multi-modal assessment, and social justice science issues etc.
Generative AI in the Software Modeling Classroom: An Experience Report With ChatGPT and Unified Modeling Language (Javier Cámara, 2024)	2024	1	The paper suggests that the use of generative AI chatbots in formative assessment can effectively gauge student learning progress. It states that the use of generative AI chatbots can increase student academic performance compared to traditional assessment methods.

Table 3: GenAI for Formative Assessments

Challenges and Ethical Considerations

As discussed in the above sections, GenAI offers immense potential in the field of education and particularly in fulfilling the objectives of NEP, 2020. However, there are some challenges and ethical concerns that must be addressed in order to ensure its responsible and effective implementation.

1. **Explainability of GenAI Models:**

The integration of GenAI in education offers promising avenues for personalised learning. However, the opaque nature of these models – often referred to as “Black Box” raise significant concerns regarding their explainability. GenAI models, particularly deep learning architectures, operate with complex internal mechanisms that are not easily interpretable. This opacity makes it challenging for educators and students to understand the rationale behind specific AI-generated recommendations or decisions (Hassan Khosravi, 2022). Making AI-models explainable would enhance learning, increase student engagement, and builds trust among educators and learners.

2. **Data Privacy and Security:**

Integrating GenAI models into educational environments introduces significant data privacy and security challenges. GenAI models often require extensive datasets, including personal and academic records (Yihao Liu, 2024). Thus, unclear policies regarding how long data is stored and when it is deleted can lead to prolonged exposure of personal information. Also, collaborations with external AI developers may involve sharing educational data, increasing the risk of data misuse or breaches.

3. **Accessibility and Digital Divide:**

AI-powered learning tools require high-speed internet and digital devices, which many rural or underprivileged students lack. Also, a disparity in digital skills can prevent certain student groups from effectively engaging with GenAI applications, thereby widening the educational gap (Bowden, 2024). There is also a possibility that educational institutions with limited funding may struggle to integrate GenAI technologies, further widening the gap between well-funded and under-resourced schools (Hancock).

4. **Bias and Fairness in AI-Generated Educational Content:**

GenAI models trained on biased datasets can produce content that reflects existing prejudices, leading to unfair representations in educational materials (Ferrara, 2023). Even with unbiased data, AI algorithms might develop biases during learning, resulting in discriminatory educational content (Ferrara, 2023). There is also a possibility that AI-generated educational materials may inadvertently reinforce societal stereotypes, affecting students' perceptions and learning experiences.

Future Research Directions

Future research directions in this regard can be focused on the following domains:

1. **Advancements in GenAI for Non-English Education:**

India is a linguistically diverse country, with 22 officially recognized languages and numerous regional dialects (Abbi, 2012). The current landscape of GenAI models is heavily skewed toward English, creating a gap in accessibility. Future research should address:

a. **Multilingual GenAI Development:** There is a need for GenAI models trained on extensive datasets in Hindi, Tamil, Bengali, Marathi, Telugu, and other regional languages to provide AI-driven learning experiences to non-English speakers.

b. **Speech and Conversational AI for Vernacular Education:** Advancements in speech-to-text and text-to-speech AI for Indian languages can make AI-driven education more accessible to students in rural and semi-urban areas. Notably Centre for Development of Advanced Computing (C-DAC) had undertaken steps to develop machine translation systems like MANTRA, AnglaMT, and MaTra to facilitate translation between English and Indian languages.

2. **Improving AI Explainability in Education:**

Research is needed to create AI systems that can provide reasoning for their generated content, ensuring educators understand how an AI-derived output was produced. Techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) can be adapted to GenAI models for better transparency (Hassan Khosravi, 2022).

Conclusion:

GenAI has the potential to revolutionize education by enabling personalized learning, a core vision of NEP, 2020. By leveraging AI-driven adaptive learning systems, content generation, and multilingual support, GenAI aligns with NEP's goals of fostering competency-based education, inclusive learning, and flexible assessment methods. Its ability to tailor educational experiences based on individual student needs ensures that learning becomes more engaging, accessible, and effective.

However, the integration of GenAI in education also brings forth significant challenges and ethical concerns. Issues such as data privacy, AI bias, digital divide, and explainability of GenAI models needs to be addressed for AI-driven learning to be truly equitable and impactful. Future research should focus on eliminating biases in AI, improving content accuracy, and ensuring accessibility for students across diverse socio-economic backgrounds. By addressing these challenges proactively, GenAI can truly fulfil NEP 2020's vision of a personalized, inclusive, and future-ready education system, empowering students to thrive in an AI-driven world.

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