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Generative Artificial Intelligence in Education: Advancing Adaptive and Personalized Learning

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Abstract

The integration of generative artificial intelligence (AI) into adaptive and personalized learning represents a transformative shift in the educational landscape. This research paper investigates the impact of incorporating generative AI into adaptive and personalized learning environments, with a focus on tracing the evolution from conventional artificial intelligence methods to generative AI and identifying its diverse applications in education. The study begins with a comprehensive review of the evolution of generative AI models and frameworks. A framework of selection criteria is established to curate case studies showcasing the applications of generative AI in education. These case studies are analysed to elucidate the benefits and challenges associated with integrating generative AI into adaptive learning frameworks. Through an in-depth analysis of selected case studies, the study reveals tangible benefits derived from generative AI integration, including increased student engagement, improved test scores and accelerated skill development. Ethical, technical and pedagogical challenges related to generative AI integration are identified, emphasizing the need for careful consideration and collaborative efforts between educators and technologists. The findings underscore the transformative potential of generative AI in revolutionizing education. By addressing ethical concerns, navigating technical challenges and embracing human-centric approaches, educators and technologists can collaboratively harness the power of generative AI to create innovative and inclusive learning environments. Additionally, the study highlights the transition from Education 4.0 to Education 5.0, emphasizing the importance of social-emotional learning and human connection alongside personalization in shaping the future of education.

Keywords

Ubiquitous learning; AI-driven education; Ethical considerations; ChatGPT; GPT-4o; Content generation; Educational transformation; Technological integration; Education 4.0; Education 5.0.

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1 Introduction

Individuals have always desired effective learning, although education is an ever-evolving field. Personalized learning aims to ensure that the educational experiences of every student are customized to their specific requirements, preferences and proficiencies (Kem, 2022). Although inspiration is not a novel concept, the methods and instruments at our disposal to manifest it have evolved substantially since the advent of technology. Artificial intelligence (AI) has brought about significant transformations in numerous domains, encompassing cultural activities and healthcare, since the beginning of the 21st century (Opderbeck, 2019). Recent advancements in artificial intelligence have been remarkable, most notably the creation of generative models capable of generating unique text and images (Bandi et al., 2023). The artificial intelligence models under consideration have demonstrated remarkable capability in imitating human creativity, occasionally producing outcomes that are identical to those produced by humans (Goldstein et al., 2023).

An unimaginable change is taking place in the world of education in the 21st century. It is becoming increasingly difficult for traditional, generic teaching methods to compete with the promise of personalized and flexible learning (Melzer, 2019). In recent years, various ways of teaching and learning have focused on individual students' ways of learning, speeds and trends to provide a personalized education that fits their needs. According to research, personalized learning can help students remember things better, understand them better and be more interested in learning (Zhang et al., 2020).

Generative AI combined with flexible learning methods has created new possibilities. Consider a situation in which AI can create learning materials at the moment, based on what a student needs (Bozkurt et al., 2023). Consider a system where tasks and quizzes are chosen automatically to challenge a student just enough based on what they already know, making the learning curve as short as possible (Alasadi & Baiz, 2023).

The area where generative AI and adaptive learning meet is changing quickly and offers both huge possibilities and difficulties. The goal of this study is to find out how difficult it is to use generative AI in adaptive and personalized learning through an investigation into the current state of the art and describing the problems that come with it. These are the research questions we want to answer with this study:

- **RQ 1:** How is generative AI being used in adaptable and personalized learning right now?
- **RQ 2:** What are the tangible benefits and successes of such applications?
- **RQ3:** Based on the comparison, what insights can be drawn about the evolving landscape of education and the potential for transformative change through generative AI?
- **RQ 4:** Which challenges and concerns are associated with the integration of generative AI in educational contexts?
- **RQ 5:** What might the future hold for the confluence of generative AI and adaptive learning?

The research questions are of a general nature, as the paper is exploratory and should encourage further discussion in this area. This paper offers a detailed exploration of the integration of generative AI with adaptive personalized learning. Section 2 introduces the foundational principles of generative AI, followed by an exposition on adaptive and personalized learning in Section 3. In Section 4, we spotlight state-of-the-art applications of generative AI in adaptive learning, detailing both its benefits and advancements. Section 5 provides an overview of AI-based educational services, coupled an with in-depth discussion of their implications. Section 6 addresses potential challenges and concerns of this integration. Future trajectories and innovations are speculated upon in Section 7, and the paper concludes in Section 8 with final reflections and key lessons.

2 Overview of Generative AI

In this section, we describe generative AI in more detail and explain how it has changed over time, starting with basic ideas in AI and ending with the latest, most advanced forms. We begin by exploring the history of artificial intelligence from the most basic methods to the new field of generative AI. Next, we reveal how generative AI works, explaining its principles in both supervised and unsupervised learning contexts. Our discussion then moves on to a full examination of popular generative AI models that have had a significant impact on the future of AI. At the end of this section, we examine how generative AI has changed over time, highlighting its historical path, breakthroughs and radical effects on technology and purposes. In general, this study will help readers comprehend the difficulties, opportunities and subtleties of generative AI.

To set the scene for our study, it is important to discuss how the sources used in this review were chosen. Peer-reviewed academic journals, reputable conference proceedings and authoritative publications in the field of AI and machine learning were the main sources that we used. Additionally, we looked at internet sites that contain a lot of information about the history, concepts and uses of generative AI.

Figure 1 shows the scope and growth of our study area to start this section. These numbers, from Scopus, show how the amount of generative AI papers has grown over the past few years. Figure 1 shows the exponential growth of published articles, which highlights the growing interest in and research into generative AI. In particularly, there is a noticeable sharp rise from 2018 to 2023, which highlights the fast progress and increased focus on this cutting-edge technology. By showing this example, we plan to set the stage for a more in-depth look at the current state of generative AI study.

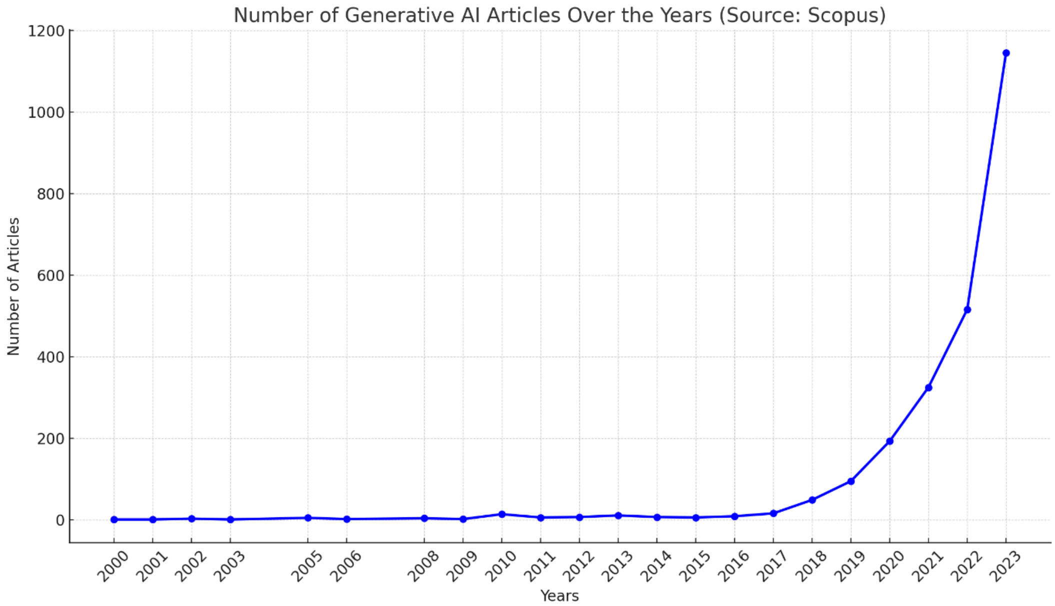

Figure 1. *Number of generative AI articles over time indexed in Scopus.*

2.1 Hierarchical evolution from artificial intelligence to generative AI

The terms artificial intelligence, machine learning and deep learning have become buzzwords in the rapidly changing field of technology and are frequently used synonymously in everyday speech (Zeadally et al., 2020). Nevertheless, despite their connections, these words refer to different aspects of a developing field in computational intelligence. Understanding the fundamental connections between these levels is crucial as we dive deeper into the realm of algorithms, neural networks and data-driven predictions. Particularly as we approach more sophisticated applications such as generative AI, this foundation becomes extremely important. We set the scene by recognizing the larger context in which these concepts have developed and thrived before delving deeper into the specifics of how they are arranged.

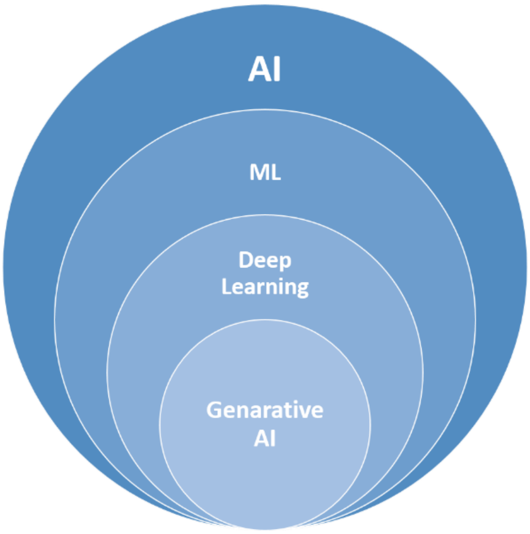

Figure 2. *Hierarchical structure of computational intelligence technologies.*

Terms such as artificial intelligence, machine learning and deep learning are frequently used interchangeably in the current computing technology area. These phrases, however, allude to several crucial phases in the creation of intelligent systems. For this reason, Figure 2 depicts the hierarchical relationship between these concepts, outlining their various functions as well as their interrelations. The graphic illustrates the evolution of various technologies over time, moving from general artificial intelligence to more specialized applications. The organization of artificial intelligence technologies is depicted in Figure 2 as a tree-like framework:

- **Artificial intelligence (AI):** Similarly to a computer system analyst, this subfield of computer science focuses on the development of systems that can perform tasks typically done by humans, as explained by Simon (1995). These tasks involve solving problems, understanding natural language, recognizing patterns and making decisions (Khanzode & Sarode, 2020).
- **Machine learning (ML):** Artificial intelligence encompasses a fascinating field where algorithms and statistical models empower systems to accomplish specific tasks without relying on explicit instructions. Instead, they depend on patterns and inferences derived from data (Zhou, 2021).
- **Deep learning (DL):** A subfield of machine learning that uses neural networks with many layers (hence deep). These models are inspired by the structure and functioning of the human brain, specifically the interconnections of neurons (Le Cun et al., 2015).
- **Generative AI:** Within the realm of deep learning, generative AI refers to models and algorithms specifically designed to generate new content or data that resemble the original training data. They capture and replicate the underlying patterns, structures and distributions of these data (Cao et al., 2023). The process of learning from existing content is known as training and it results in the development of a statistical model. When given a prompt, generative AI uses this statistical model to predict what an expected response might be and this results in the generation of new content (Brynjolfsson et al., 2023).

2.2 Functions of generative AI in supervised and unsupervised learning

The intricacies of generative AI operation is explained below, placing it within the core frameworks of supervised and unsupervised learning. As we move through this inquiry, we hope to shed light on the distinct approaches and goals of each paradigm, paying particular attention to the contribution of each to the field of artificial intelligence.

- **Supervised learning:** Models are trained using labelled data in supervised learning (Cunningham et al., 2008). This entails associating each input sample from the training dataset with its corresponding output. The principal aim is to gain insight into the correlation between inputs and outputs, which facilitates the generation of precise predictions on unfamiliar data (Hastie et al., 2009). Regression and classification tasks are two such examples in which the performance of the model can be explicitly assessed in comparison to the ground truth labels.

- **Unsupervised learning:** Unsupervised learning operates in the absence of labelled data. The foundation patterns or structures within the dataset are what the model aims to discern. This learning approach is illustrated by techniques such as *k*-means clustering (Pham et al., 2005) and principal component analysis (PCA) (Wetzel, 2017). Uncovering concealed patterns or structures in the data without relying on predefined labels is the primary objective.
- **Generative AI:** Generative models are distinct from both supervised and unsupervised learning (Hitawala, 2018). Although they can be trained without supervision, their main goal is distinct (Han et al., 2018). Generative models focus on capturing the underlying probability distribution of the data, rather than simply predicting labels or identifying data structures (Peis et al., 2023). Once this distribution is grasped, the model can generate new data instances that closely resemble the training data (Nah et al., 2023). They can generate innovative and logical content, whether it is in the form of images, text, video, code or any other type of data (Zhang et al., 2023).

Figures 3 and 4 together provide a comprehensive overview of the evolution from traditional machine learning to generative AI models.

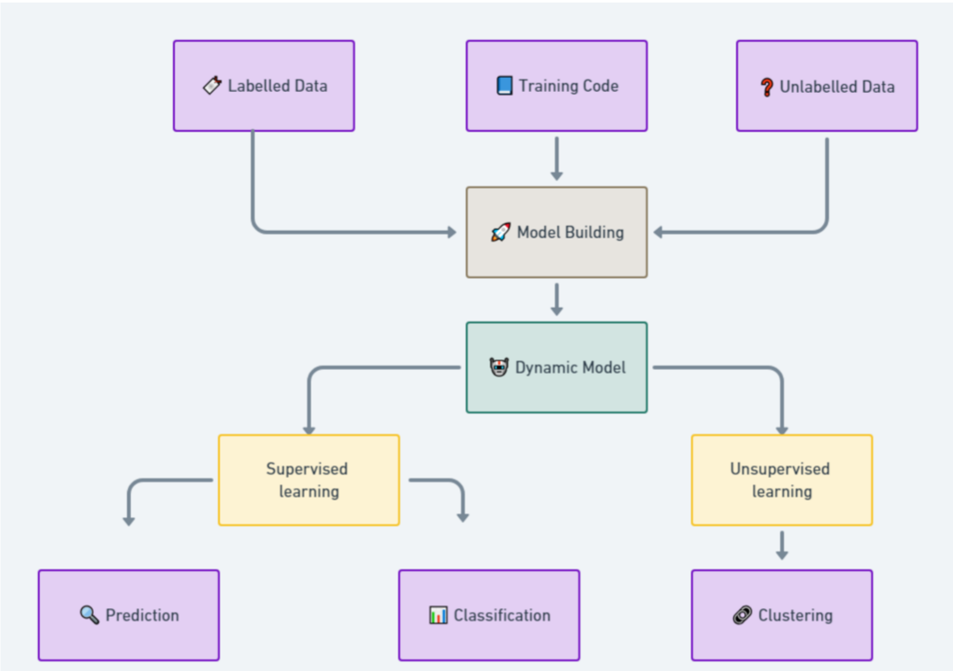

***Figure 3.** Machine learning concepts.*

Figure 3 provides a visual representation of the machine learning workflow, emphasizing both supervised and unsupervised learning. It highlights the crucial importance of training code, labelled data and unlabelled data. The sequence begins with these inputs converging in the model building phase. This process results in a dynamic model that can perform key tasks associated with both types of learning. For supervised learning, which uses labelled datasets, the model acquires the ability to make informed predictions and classifications. In contrast, the unsupervised learning pathway utilizes unlabelled data to enable clustering. This dual approach demonstrates the versatility and comprehensive nature of the machine learning process.

In contrast, Figure 4 represents a more sophisticated and expansive framework. It retains elements from the traditional machine learning approach, such as training code and labelled data, but introduces unlabelled data into the mix. This inclusion allows the integration of both supervised and unsupervised learning modalities. The unlabelled data are fed into the foundation model, which serves as a versatile base capable of generating a variety of content forms, including text, code and images. This foundation model underscores the flexibility and broad applicability of generative AI.

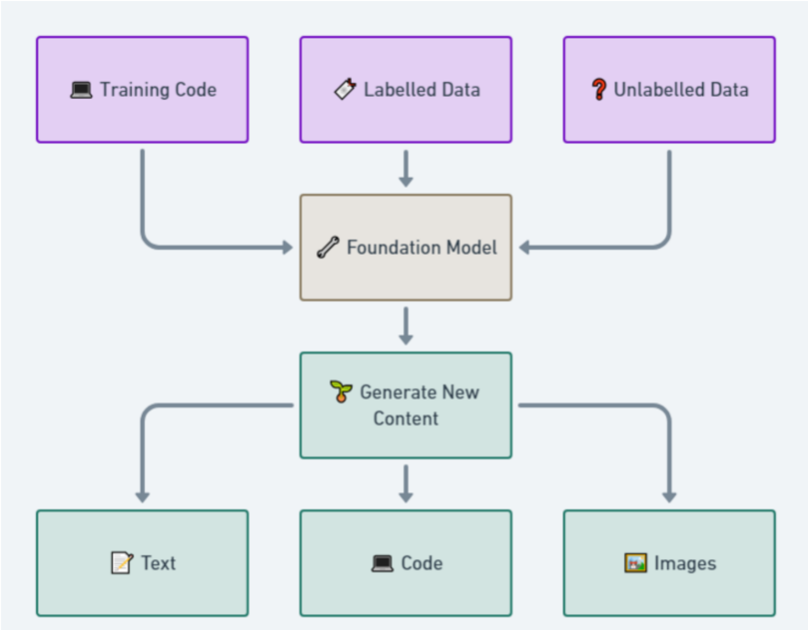

Figure 4. *Generative AI process.*

The key distinction highlighted in Figure 4 is the generative capabilities of the model. Unlike the traditional model in Figure 3, which is largely tethered to prediction and classification, the foundation model in Figure 4 exhibits the ability to produce novel content. This generative aspect represents a significant departure from the predictive or clustering functions of models solely grounded in supervised or unsupervised learning. In summation, while the traditional machine learning model depicted in Figure 3 focuses primarily on supervised learning, Figure 4 encapsulates a more holistic view. It encompasses both supervised and unsupervised learning, distinguishing itself by its generative capabilities. Generative AI, as illustrated in Figure 4, not only learns and understands but also creates, paving the way for a new frontier in artificial intelligence.

2.3 Generative vs. discriminative models

Generative models, typified by techniques such as variational autoencoders (VAEs) (Girin et al., 2021) and generative adversarial networks (GANs) (Goodfellow et al., 2020), endeavour to capture the underlying probability distribution of input data. By mastering the intricacies of dataset structures, generative models possess the remarkable ability to create new samples that mimic the characteristics of the training data (Regenwetter et al., 2022). Their utility spans a wide spectrum of domains, including image synthesis, text generation and anomaly detection.

Conversely, discriminative models (Zheng et al., 2023) are in place to establish decision boundaries between distinct classes in the input data. These models include support vector machines (SVMs) (Noble, 2006) logistic regression (Kleinbaum & Klein, 2002), linear regression (Weisberg, 2005), decision trees (Magee, 1964), neural networks (Abdi et al., 1999) and others. Discriminatory models prioritize the accurate classification of data elements according to their features (Zheng et al., 2023), as opposed to modelling entire data distributions. Classification tasks encompass a diverse array of applications, including but not limited to image categorization, sentiment analysis and spam detection.

In addition to generating new data samples, generative models discover the joint probability distribution of input and output factors. By contrast, discriminative models are utilized to sort data into groups and concentrate on discovering the boundary of decision-making that separates classes. Which of these two approaches is utilized is determined by the requirements of the task, the nature of the data and the intended outcomes.

2.4 Defining concepts in generative AI

It is the forefront of technology that machines can create data and material on their own, thanks to generative artificial intelligence (AI) (Rane, 2024). It is important to understand basic ideas such as foundation models (Moor et al., 2023), pre-training (Radford et al., 2018), fine-tuning (Han et al., 2024), prompts (Han et al., 2024), parameters (Peeperkorn et al., 2024) and overfitting (Variš & Bojar, 2021) to work well in this complicated area. In this section, we go into more detail about these basic ideas and explain what they mean and how they can be used in generative AI. Scientists and professionals can learn more about functioning of generative models by breaking down these ideas. This will help them make better decisions and lead to new ideas in AI-driven content creation.

Foundation models

A foundation model is the foundational structure or design that a generative AI model employs to generate data autonomously (Moor et al., 2023). GPT (generative pre-trained transformer) and variational autoencoders (VAEs) are transformer-based designs (Dogan et al., 2023) that generate adversarial networks (GANs). Particular characteristics of each foundation model render it ideal for generating specific forms of data, such as text, images or other formats of content.

Pre-training

Within generative AI, pre-training is an important step in which a model learns basic features and patterns on a big, varied collection (Moor et al., 2023). Before fine-tuning specific tasks, this pre-training step gives the model a chance to learn a lot about the subject. The model can learn from unstructured data using self-supervised learning or guided learning with extra tasks to help feature learning (Moor et al., 2023).

Fine-tuning

Within generative AI, fine-tuning refers to training a pre-trained model more on a specific assignment or dataset so that it can change to the specifics of that task (Han et al., 2024). After the original pre-training, the model parameters are often updated using task-specific data at a reduced learning rate. Because fine-tuning allows application of the model knowledge to the current task, it improves performance and efficiency (Howard & Ruder, 2018).

Prompts

For generative AI, a prompt is an indicator or input that relates the model to produce results that meet certain requirements (Heston & Khun, 2023). Prompts can be anything from simple text messages to more complicated instructions or conditioning data, based on the model and the desired result. Supporting the generation process to proceed quickly and getting the model to respond appropriately depends on creating excellent prompts. They are zero-shot (Fahes et al., 2023), one-shot (Fahes et al., 2023) and few-shot (Schick & Schütze, 2022). Without any extra training or examples, zero-shot suggests giving a model a question and expecting it to come up with relevant content. A single instance of the desired result is provided in a one-shot request. Few-shot prompts give a short list of examples or cases related to the desired output.

Parameters

Parameters are crucial in determining the functioning and capacities of large language models (LLMs). In this context, parameters are the customizable elements in the model that are tuned during training to improve its performance in natural language processing tasks (Shoeybi et al., 2019). The criteria usually encompass:

- embedding matrices (Hoffmann et al., 2022)are used to represent words or tokens as dense vectors in a high-dimensional space, which helps improve semantic understanding;
- attention mechanisms are responsible for controlling the capacity of a model to concentrate on important segments of input sequences. This is particularly important for tasks such as machine translation and summarization (Wang et al., 2019);
- feedforward neural networks are employed in transformer designs to process information and provide outputs depending on acquired representations (Naveed et al., 2023); and
- layer normalization and activation functions are crucial for maintaining stable training and efficient signal propagation inside the model (Ding et al., 2023).

The selection and optimization of these parameters have a substantial impact on the model performance, including accuracy, inference speed and memory efficiency. Practically, it is crucial to comprehend and optimize these factors to customize huge language models for specific uses and enhance their effectiveness in other fields.

Overfitting

Overfitting in large language models (LLMs) refers to the phenomenon where the model overly memorizes the training data, resulting in a diminished capacity to generalize to unfamiliar data (Zhu & Rao, 2023). This phenomenon can have a substantial influence on the dependability and efficiency of LLMs in practical situations. The elements that contribute to overfitting in linear regression models include model complexity, as language models that contain a large number of parameters and layers are prone to overfitting since they possess the ability to retain irrelevant information included in the training data (Yang et al., 2023). The size of the training dataset is inadequate to the complexity of the model, which might worsen overfitting and restrict the model capacity to generalize beyond the training set. Improper configuration of hyperparameters or extremely extended training periods can result in overfitting when the model becomes too specialized on the training data (Tirumala et al., 2022).

2.5 Generative AI models

In the following section, we delve into the intriguing world of generative AI models. These models, true to their name, specialize in crafting new data that have never been seen before. Distinct from discriminative models, which discern differences in data, generative models master the inherent distribution of data. Once they acquire this knowledge, they can draw samples from the distribution, resulting in new instances that echo the characteristics of the input but are not exact duplicates.

2.5.1 Key generative AI architectures

Table 1 below offers a comprehensive insight into the pivotal generative AI architectures, shedding light on their definitions and predominant uses.

Table 1. *Key generative AI architecture.*

Architecture	Description	Applications
Generative adversarial networks (GANs)	Conceived by Ian Goodfellow and his team in 2014, GANs encompass two neural entities: the generator and the discriminator. The generator endeavours to fabricate counterfeit data, while the role of the discriminator is to discern the genuine from the counterfeit. These competitive dynamics hone the generator skill in crafting increasingly authentic data (Creswell et al., 2018).	Image generation, style transfer and data augmentation
Variational autoencoders (VAEs)	VAEs offer a probabilistic perspective on autoencoders. Their mission is to encapsulate data in a latent realm and then revert them. VAEs integrate a probabilistic element, ensuring that latent representations adhere to a particular distribution, usually Gaussian (Doersch, 2016).	Image generation, anomaly detection and generating structured data
Transformer-based generative models	The inception of transformer structures, particularly models such as GPT by Open AI, revolutionized natural language processing. Pre-trained on extensive text data, these models are adept at generating text that is both coherent and context-sensitive (Yang et al., 2021).	Text generation, content creation, chatbots

2.5.2 Generative AI based on data

Generative AI models, designed to produce data resembling their training sets, encompass generative language models (GLMs) (Karabacak et al., 2023) and generative image models (Assogba et al., 2023), such as those presented in the mind map Figure 5. GLMs, exemplified by the GPT series developed by OpenAI, such as GPT-3 (Binz & Schulz, 2023) and GPT-4 (Mao et al., 2023), aim to generate coherent text, with applications spanning text translation, summarization, question-answering, grammar correction, image and video generation, text-to-speech and game playing. On the other hand, generative image models, notably GANs and style GANs, focus on creating or modifying images. Their applications include image captioning, visual question answering, image search, super-resolution, image completion and animation.

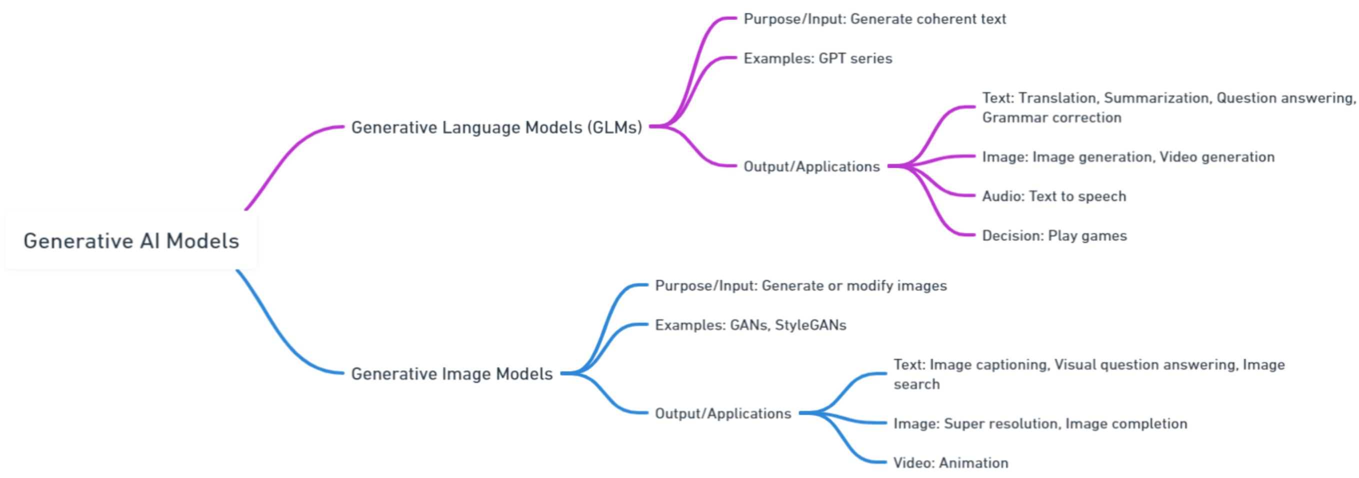

Figure 5. *Mind map of types of generative AI based on data.*

2.6 Evolution of generative AI

The evolution of generative models in artificial intelligence continues to advance rapidly, with recent developments bringing forth new milestones and capabilities. From the foundational architectures of GANs and VAEs to the groundbreaking models from OpenAI, such as GPT-3, GPT-4 and GPT-4o, the landscape of generative AI is continually evolving. Several emerging frameworks, including Llama (Touvron et al., 2023), Ollama (Gruber & Weber, 2024), Mistral7B (Jiang et al., 2023) and Phi3 (Abdin et al., 2024), not only augment the capabilities of well-established models but also extend the potential of text generation and multimodal inference engineering. Local deployment of complex language models, web navigation and dialogue systems are a few of the applications for which these models offer a vast array of capabilities and features tailored to their particular requirements. As the introduction of these novel models is examined, one can discern the ongoing advancements in artificial intelligence (AI), which present captivating resolutions and revolutionary developments across various domains.

Table 2. *Generative models from early innovations to modern milestones.*

Model	**Year**	**Key features**	**Primary applications**	**Description**
RNN (recurrent neural network)	The early 1990s	Uses loops to remember previous information	Text generation, time-series prediction	RNNs have loops that keep information relevant (Alam et al., 2023). They can be used for, e.g., language models and finding patterns.
VAE (variational autoencoder)	2013	Uses a probabilistic approach to generate data	Data reconstruction, anomaly detection	VAEs are probabilistic models that encode input data into a latent space, which is then decoded to recreate the input (Doersch, 2016). They can generate new instances that share characteristics with the training data.
GAN (generative adversarial network)	2014	Two neural networks (generator and discriminator) in competition	Image synthesis, art creation	GANs consist of two competing networks: a generator, which creates images, and a discriminator, which evaluates them (Creswell et al., 2018). The two networks are trained together in a cat-and-mouse game.
NLP and transformers	2017	Uses self-attention mechanisms	Text generation, translation, content creation	Transformers, especially models such as GPT, utilize self-attention mechanisms to weigh input data differently, making them highly effective for various NLP tasks (Patwardhan et al., 2023).
Flow-based models	2018	Uses invertible transformations to model data distribution	Density estimation, generative tasks	Flow-based models use a series of invertible transformations to model the data distribution directly, enabling efficient sampling and density estimation (Yin et al., 2023).
GPT-3 (generative pre-trained transformer 3)	2020	Transformer-based model with 175 billion parameters	Text generation, code writing, task-specific applications	GPT-3 set a new benchmark in the realm of generative models with its vast parameter count and ability to handle diverse tasks without task-specific training (Binz & Schulz, 2023).
DALL·E	2021	Variant of GPT-3 tailored for visual content generation	Image synthesis from textual descriptions	DALL·E, a variant of GPT-3, demonstrated the capability to generate creative visual content from textual prompts, bridging the gap between text and imagery in AI (Gamoura et al., 2024).
Megatron-Turing NLG by NVIDIA	2022	Large text generation model	Text generation, dialogue systems	This model excels at generating large amounts of text, potentially for applications such as creating scripts or dialogue for chatbots (Yin et al., 2023).
GPT-4 (generative pre-trained transformer 4) from OpenAI	2023	Transformer-based model with an even larger parameter count and improved capabilities	Advanced text generation, few-shot learning, broader applications	GPT-4, building on its predecessor, offers enhanced performance and better generalization and can be fine-tuned for specific applications more effectively (Mao et al., 2023).
Mistral7B	2023	7B parameters, 4.1GB size	Web navigation, dialogue and human-centric browsing	A language model developed by Mistral AI focused on web navigation and human-centric browsing is available on the Hugging Face Model Hub (Jiang et al., 2023).

Model	Year	Key features	Primary applications	Description
Llama 3	2024	70B parameters, 40GB size	Text generation, multimodal inference engineering	A high-performance language model developed by Meta suitable for local deployment (Huang et al., 2024).
Ollama	2024	Open-source framework supporting various LLMs	Local deployment of large language models, development and research	An open-source framework for running large language models locally, providing an integrated platform for developers and researchers (Gruber & Weber, 2024).
Phi3	2024	3.8B parameters, 2.3GB size	Small but high-performance language model	A smaller language model developed by Microsoft, designed for efficiency and performance (Abdin et al., 2024).
GPT-4o	2024	GPT-4o attains GPT-4 turbo-level proficiency in text, reasoning and coding intelligence, while surpassing previous benchmarks in multilingual, audio and visual skills	Enables voice mode to engage in conversation using ChatGPT	GPT-4o, short for GPT-4 omni, represents a significant advancement in human-computer interaction by allowing input in many forms such as text, audio, image and video and generating outputs in any combination of text, audio and picture (OpenAI, 2024).

2.6.1 Discussion

Table 2 shows an overview of changes in generative models over time, showing the development from early ideas to modern advances. The latest models released in 2024 are very different from the earlier ones because they have many more factors or tokens. This demonstrates the increasing size and strength of the models. As an illustration, Llama 3 possesses a staggering 70 billion parameters, Ollama enables the deployment of several large language models locally, Mistral consists of 7 billion parameters and Phi3 is a comparatively smaller model with 3.8 billion parameters. For more complicated and nuanced generation tasks, this rise in parameters shows that both model design and training methods have improved. In addition, the focus on token count shows the importance scaling and speed for current generative models, which allows them to perform better on more tasks and datasets. Overall, these new developments are a big step forward for generative AI, opening possibilities for more advanced uses in many areas.

3 Adaptive and Personalized learning

Innovative ideas in education such as adaptive and individual learning are not new. Teachers have long wanted to make sure that each student's learning experiences are tailored to their specific needs, tastes and skills (Radford et al., 2018). In standard classrooms, this meant that teachers had to track each student's growth closely and change lessons as needed. Unfortunately, it became harder to provide truly flexible and personalized learning on a large scale as the number of students and their learning needs increased.

This problem has been solved by technology in recent years: flexible learning systems. Using algorithms, these systems change a student's learning path based on how well they do, making sure they do not get bored with too easy material or stressed out by too difficult material. It is the goal of personalized learning to make the learning experience more meaningful and engaging by adapting it to the learner's interests, goals and chosen learning style.

Next, we overview the background on the sources we used. Most of the information utilized in this section was collected from esteemed scholarly publications, widely recognized educational resources and conference papers pertaining to education, educational technology and artificial intelligence. In addition, we examined websites that provided extensive knowledge on the historical background, fundamental principles and practical applications of adaptive and customized learning. Our objective was to provide readers with a comprehensive understanding of the subject matter by using a diverse range of published sources.

3.1 Adaptive learning

According to Wang et al. (2023), adaptive learning is a new way of teaching and learning that changes to fit each student's current performance. Using complicated algorithms and data analysis, this method constantly checks a student's interactions, answers and progress, changing the content, level of difficulty and resources as needed. With this, the learner's current knowledge and skills are kept in mind throughout the learning process, which promotes efficiency and focused growth.

3.2 Personalized learning

Traditional teaching methods are not as effective as personalized learning (Watters, 2023), which creates a learning path for each student based on their likes, dislikes and goals. In contrast to focusing only on academic success, this all-around method looks at the learner's whole experience. Emotional and social factors are also taken into account, along with their chosen learning style and the speed at which they are most relaxed. With this, the student becomes more interested, driven and self-aware (Dogan et al., 2023).

3.3 Importance of using technology in education

The 21st century has witnessed an unprecedented surge in technological advancements, and these changes have permeated nearly every aspect of our lives including education (Guettala et al., 2023). The integration of ubiquitous technology in educational settings offers several benefits:

- **Scalability:** Digital platforms can cater to millions of students simultaneously, democratizing access to quality education with the use of cloud computing (Guettala et al., 2022).
- **Flexibility:** Online learning platforms enable students to learn at their level and in their own time, freeing them from the constraints of traditional classroom schedules; this is the concept of ubiquitous learning (Guettala et al., 2021).
- **Data-driven insights:** Technology enables the collection and analysis of vast amounts of data, offering insights into student performance, areas of struggle and potential interventions (Dhoni, 2023).
- **Interactivity:** Advanced technologies such as augmented reality (AR) and virtual reality (VR) can make learning more immersive and interactive (Chheang et al., 2024).

However, simply digitizing traditional content does not fully realize the technological potential. True innovation occurs when advanced technologies, such as artificial intelligence, are used to transform the learning experience.

4 Generative AI for Adaptive and Personalized Learning

In this section, we delve into the transformative potential of generative AI in reshaping adaptive and personalized learning in education. The content emphasizes the rise of generative AI research in education, as demonstrated by a surge in related articles in 2023. Our selection of sources for this section was based on a comprehensive review of reputable academic journals, authoritative textbooks and relevant conference proceedings in the fields of education, artificial intelligence and educational technology.

Generative AI changes the production of material, evaluation and giving of feedback by automating, personalizing and adapting in real time. By combining ideas from many different research works, we created an exhaustive overview of ways to use generative AI in these areas.

Using new research and theoretical models in the field, this part also talks about the ability of generative AI to predict best ways to optimize learning paths. We tried to include a range of points of view and case studies to show how generative AI could improve students' highly customized and adaptable learning experiences.

The part ends with a comparison of the features of generative AI with normal teaching methods. The advantages and disadvantages of this combination are pointed out, using actual scenarios and expert views from the literature.

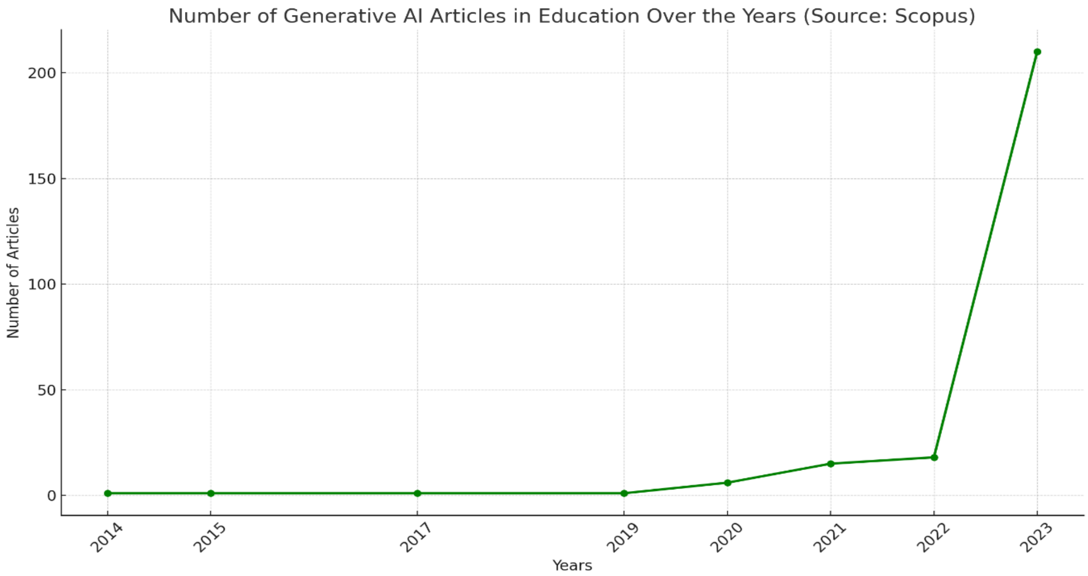

Figure 6. *Number of generative AI articles in education over time indexed in Scopus.*

Figure 6 shows the progression of articles on generative AI applied to education from Scopus over time. This gives us an idea of the application of generative AI in education. Generative AI is becoming increasingly popular in educational institutions, as shown by the sharp rise in 2023. Generative AI can change education and this rise shows that more and more people are realizing this.

4.1 Generative AI in content creation

Generative AI has changed content production by giving us tools that can automatically and personally customize a huge amount of teaching content. They can divide these improvements into two primary categories:

A. Automated generation of questions, assignments and learning materials

- **Question generation:** The information can be looked at by AI models, which can then generate questions automatically, including both multiple-choice and short-answer questions (Kurdi et al., 2020). Along with saving teachers time, this system makes sure that tests have a wide range of questions.
- **Assignment generation:** The generative models possess capabilities beyond inquiry; they can also generate complete assignments that are tailored to the current curriculum and ensure adherence to learning objectives and standards (Gimpel et al., 2023).
- **Learning material production:** Working simulations, diagrams and educational aids can be produced by generative AI. For instance, AI can transform a text-based lesson into one that is

more engaging or visually stimulating, which is beneficial for students who learn best by doing or seeing things (García et al., 2023).

B. Personalized content for different learning styles and paces

- Generative AI can change material to fit different learning styles by using information about each student's success and preferences. Audio learners might get podcasts or narrated slides, while visual learners might get more images and movies (Leiker et al., 2023).
- Generative models can also change the speed of information dissemination. Individuals who learn faster may get condensed forms or more advanced materials, while those who learn more slowly may get more thorough descriptions or extra practice materials.

4.2 Generative AI in assessment and feedback

The evaluation process, which used to depend largely on educators' statements has been greatly improved by the addition of generative AI:

A. Automated grading systems

- Generative models can be taught to understand precisely how individuals react (Doo et al., 2023). Their ability to grade both objective questions, such as multiple-choice tests, and more emotional ones, such as writing, is increased.
- These methods also dispose of teachers' and administrators' personal preferences, so the work of students is graded more fairly.

B. Personalized feedback generation

- Generative AI can make specific feedback for each student's entry instead of universal feedback (Nysom, 2023). As a result, the input is useful and closely related to the student's areas that need work.
- Any student can choose from writing, audio comments or visual notes as a feedback style.

4.3 Generative AI in learning path optimization

Generative AI models can identify and suggest the best learning paths by using data from thousands of students:

A. Predictive modelling for optimal learning trajectories

- Generative AI can figure out the best order of topics or units for each student by looking at the trends of successful learners (Ivanovic et al., 2021).
- These predictions can also take into account how well a student did in the past, making sure that the suggested path is both hard and doable.

B. Personalized course recommendations

- A student's hobbies, goals and academic history can help generative AI suggest courses or topics that are a good fit for them (Wang et al., 2023).
- These suggestions may change over time based on the student's choices and results.

As a result of contemporary generative AI for adaptable and specialized learning, the delivery and experience of education have been profoundly transformed. Generative AI increases the likelihood of success by customizing education to each individual's specific requirements through the implementation of automation, personalization and enhancement of various learning process components.

4.4 Discussion

The progression of the impact of generative AI on the learning environment is illustrated in Figure 7. This study delineates three critical domains in which the most substantial impacts of generative AI have been observed: content development, testing and providing feedback, as well as enhancing the learning path.

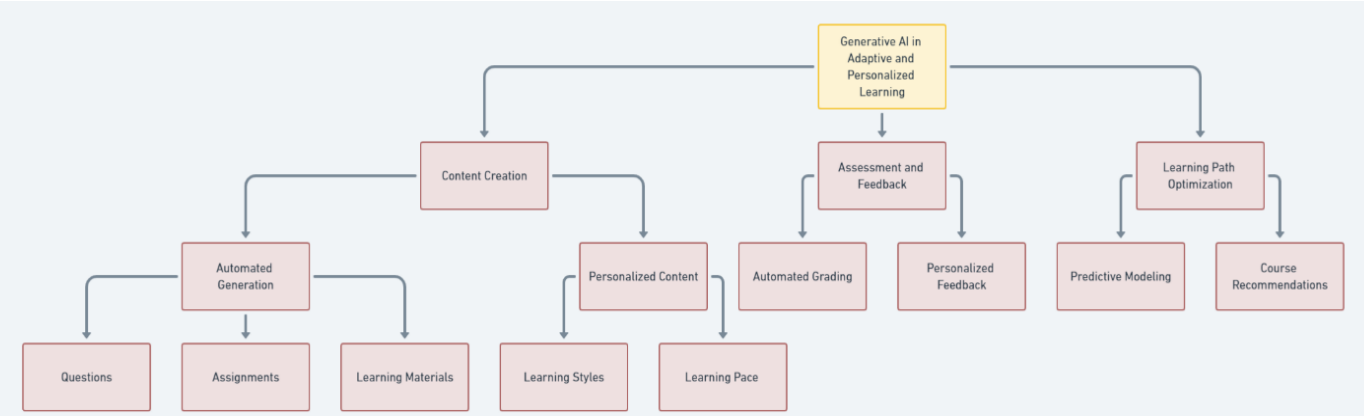

Figure 7. *Detailed study of generative AI in personalized learning.*

The implementation of generative AI in the domain of content creation is critical for automated development of instructional materials and personalization of content for each individual. AI could fundamentally alter the content creation process, as evidenced by its capacity to generate quizzes, assignments and various types of learning materials such as diagrams, readings and compelling models. This increases the variety of instruments available to students and simplifies matters for instructors. In addition to its adaptability, generative AI permits the modification of content to accommodate various learning methods and rates. For instance, visual learners may benefit more from narrated material than from recordings, while auditory learners may find narrated material more beneficial than diagrams and videos. Students are prevented from being overly occupied or squandering their time due to the adaptable schedule.

Significant progress has also been made in the domains of evaluation and input as a result of generative AI. Systems powered by artificial intelligence are now capable of autonomously grading responses to a wide range of questions, including complex writings and simple multiple-choice questions. This reduces the influence of personal preferences and accelerates the grading process, resulting in more accurate and objective grades. Additionally, students receive more targeted and beneficial feedback than before. By analysing each submission individually, generative AI is capable of providing feedback that precisely targets areas requiring development, thereby meeting the unique requirements of each student. Learning path optimization makes use of the enormous data processing capacity of generative AI. By analysing data from large numbers of students, the models are able to conjecture and recommend the most effective learning paths. By considering patterns observed in high-achieving students as well as the student's historical performance, this type of predictive modelling ensures that the recommended course of action is challenging yet achievable. Generative AI recommends entire courses or subjects that align with a student's evolving academic background, personal interests and aspirations, as opposed to merely proposing individual topics.

Generative AI combined with adaptable and personalized learning signals the start of a new age in education. Due to its ability to automate, personalize and improve many parts of learning, generative AI promises that students around the world will have more streamlined, personalized and improved learning paths. The benefits of using generative AI with adaptive learning are summarized in Table 3.

***Table 3.** Benefits of integrating generative AI into adaptive learning.*

Benefit	Description
Enhanced student engagement	Personalized content resonates with individual learning styles and interests, leading to higher engagement and retention rates (Peñalvo et al., 2023).
Reduced workload for educators	Automation of tasks such as content generation, grading and feedback provision frees educators to focus on core teaching activities and student interactions (Whitham et al., 2018).
Scalability for large-scale education platforms	Generative AI offers solutions that maintain quality and personalization even when catering to millions of students, ensuring consistent educational experiences across large audiences (Baidoo-Anu & Ansah, 2023).
Continuous learning and real-time adjustments	The dynamic nature of generative AI allows immediate adaptation based on student performance (Mills et al., 2023). This ensures timely support and resources, facilitating an environment where learning is continuously optimized based on real-time needs and feedback.

Using a comparison view, we can sum up the differences between the role of generative AI in adaptive and personalized learning and the old ways of managing adaptive and personalized learning. Using this comparison is a key part of knowing how generative AI is changing schooling globally. Although standard methods have their good points and are based on years of experience in teaching, generative AI brings about a new way of doing things that seems to be more flexible and tailored to everyone. Table 4 provides a summary of these differences and a clear comparison of features, flexibility, growth and other important factors.

***Table 4.** Comparison of generative AI and traditional adaptive learning methods.*

Aspect	Generative AI in adaptive learning	Traditional methods with adaptive learning
Content creation	Automated	Manual
Adaptability	Real-time	Periodic
Scalability	High (AI-driven)	Limited
Feedback	Instant (AI-driven)	Delayed (human-driven)
Personalization	Deep	Broad
Data dependency	High	Low
Tech integration	Seamless	Variable
Ethical concerns	Data privacy, biases	Pedagogical ethics

Table 4 shows the benefits and problems of using AI in educational organizations. Although generative AI offers automation, the ability to change in real time and deep personalization, it is highly data-driven, which raises privacy and bias concerns. Although traditional methods are based on effective teaching methods, they often fail when it comes to scalability and flexibility in real time. Because of this, a balanced method is needed that takes advantage of the strengths of both theories while minimizing their weaknesses. Due to the rapid pace of changes in the educational world, this comparison can help teachers and engineers make learning better.

5 Overview of AI-based Educational services

This section explores several selective overviews of AI-based services that can be used in education. They show that generative AI can completely change adaptive and personalized learning. It demonstrates how flexible AI apps can be in many areas of education and how well they can personalize the learning process. We chose these case studies because they are related to the topic of generative AI in flexible and personalized learning. It shows the current uses of generative AI to improve learning in a variety of educational areas through eight different platforms. To give an exhaustive overview of the many ways generative AI can be used in education, these case studies were considered necessary.

5.1 Selection criteria

The illustrations in Table 5 show the increasing current use of generative AI in adaptable and personalized instruction on a variety of educational platforms. The degree of adaptability represented by generative artificial intelligence applications is demonstrated by the careful selection of these platforms. The selection of these case studies was based on several criteria, including their applicability as examples, diversity of domains, emphasis on personalization and success metrics. The case studies were selected using the subsequent criteria:

- **Domain diversity:** The selected platforms include those for higher education, language learning, mathematics, interview coding, conversational AI, personal assistant for educators and concept map creation. Generative AI can facilitate effective learning for learners of all ages and from all disciplines, as evidenced by the breadth of subjects covered.
- **Personalization focus:** For each platform, AI is employed to personalize the learning experience by adjusting the difficulty level, instructional approach and available learning materials to align with individual students' preferences and learning modalities. Those who specialize in education technology may recommend adaptable resources, while language learners may utilize personalized practice queries.
- **Success metrics:** According to case studies, implementing generative AI produces positive outcomes, such as increased student engagement, higher test scores and faster skill development. AI-driven personalization enhances the learning process, as evidenced by these metrics.
- **Illustrative potential:** Specific platforms demonstrate the implementation of generative AI in flexible learning through the generation of one-of-a-kind practice questions, recommendation of learning materials and provision of immediate feedback, among other functions. This example demonstrates the versatility of generative AI in facilitating adaptable learning.

5.2 Overview

Generative AI combined with adaptable, individualized learning methods represents a paradigm shift in the current educational system and has the potential to revolutionize instruction. For instance, while conceptual frameworks illustrate potential pathways, the practical implementation of these combinations reveals both their benefits and challenges. In this section, an overview of AI-based services that can be used in education is examined, showcasing platforms that have effectively incorporated generative AI into their academic structure. We aim to provide a comprehensive analysis of how generative AI is simultaneously advancing and disrupting conventional teaching methods through an examination of their achievements, shortcomings and unforeseen revelations.

Table 5. *Implementation of adaptive learning via generative AI.*

Platform	Domain	Generative AI model used	Application in adaptive and personalized learning	Success metric/lesson learned
Duolingo (Goodwin et al., 2022)	Language learning	Proprietary model	Uses AI to adapt lessons based on user performance and learning speed.	Increased user engagement and faster language proficiency
Knewton (Wu & Mao, 2023)	Education technology	Proprietary adaptive learning engine	Provides personalized recommendations for learning resources based on student performance.	Improved student outcomes in courses

Platform	Domain	Generative AI model used	Application in adaptive and personalized learning	Success metric/lesson learned
DreamBox (Foster, 2023)	Math education	Proprietary model	Adapts math lessons in real time based on student interactions.	Students using DreamBox saw a 60% improvement in test scores.
Smart Sparrow (Abe, 2023)	Higher education	Adaptive e-learning platform	Offers adaptive e-learning platforms for higher education.	Institutions reported higher student engagement and understanding.
ChatGPT 3.5 (Rasul et al., 2023)	Conversational AI	GPT-3.5	Generative AI model used for various applications including tutoring and answering questions	Enhanced user experience with more accurate and diverse responses
ChatGPT 4 (Temsah et al., 2023)	Conversational AI	GPT-4	Improved version of ChatGPT with better understanding and response generation	More coherent and context-aware responses, better handling of complex queries
Labster (Mayer et al., 2023)	Virtual science labs (science simulations)	Custom-built AI for creation of dynamic virtual labs	Generates simulations that adapt to student choices and actions within the virtual lab environment.	Increased student engagement and understanding compared to traditional labs
Italki (Italki, 2024)	Language learning with human teachers	Pre-trained language models combined with user data	Personalizes learning experience by recommending human tutors and generating personalized practice materials.	Faster language fluency gains compared to traditional methods
ASSISTments (Koedinger et al., 2010)	Personalized tutoring system for math coursework	Rule-based AI system combined with natural language processing	Provides immediate feedback on student problem-solving and generates hints based on mistakes.	Improved problem-solving skills and higher scores in math exams
Codility (Zamfir & Pricop, 2022)	Coding interview preparation and skill development	Machine learning and natural language processing	Generates personalized coding challenges and provides real-time feedback.	Significant improvement in coding skills and interview performance
Gemini (Google, 2024) *Claude3* (Anthropic, 2024) *Copilot* (Microsoft, 2023) *Cohere* (Gomez, 2019) *POE* (Grinding, 2023) *Groq* (Ross, 2016) *Perplexity* (Srinivas, 2022,)	Conversational AI	Proprietary model	Provides personalized learning experiences across various educational domains.	Enhanced multimodal understanding, content generation capabilities, programming proficiency, language proficiency, communication skills, problem-solving abilities and critical thinking skills

Platform	Domain	Generative AI model used	Application in adaptive and personalized learning	Success metric/lesson learned
Magic School (Khan, 2023) *SchoolAI* (Hicks, 2023)	Personal assistant for teachers to complete department tasks	Proprietary model	Employs generative AI as a personal assistant for teachers, assisting in completing departmental tasks such as lesson planning, grading, scheduling and administrative duties.	Improved administrative processes, task management and productivity for teachers, enabling them to efficiently manage departmental tasks such as lesson planning and curriculum development
Chat PDF (Lichtenberger, 2023) *Explainpaper* (Asmus, 2023) *Elicit* (Ought, 2023)	Chat with PDF	Proprietary model	Integrates generative AI into chatbot platforms to enable interactive conversations and assistance with PDF documents, offering real-time guidance and support to learners.	Improved accessibility and usability, allowing users to easily access and engage with content, thereby enhancing comprehension and knowledge retention
Socrative (Showbie, 2024) *Diffit* (Black, 2023) *Conker* (Mote Technologies, 2023) *GPT-4o* (OpenAI, 2024)	Student assessment and immediate feedback	Proprietary model	Uses generative AI for student assessment, providing immediate feedback on assignments, quizzes and exams. This facilitates timely intervention and personalized guidance. Utilizes voice mode to engage in real-time problem-solving discussions using ChatGPT. This feature is designed to assist students in comprehending solutions to educational problems by providing an easy and adaptable learning experience.	Enhanced student engagement and comprehension through interactive assessments and real-time feedback
Socratic (Greek philosopher, 2023) *Sizzle* (Pesenti, 2023) *Studdy* (Lam, 2023)	AI-powered teacher's assistant for homework correction	Proprietary model	Utilizes generative AI to create AI-powered teacher assistants capable of correcting homework assignments, providing detailed feedback and guiding students towards improvement.	By implementing a personalized learning environment, facilitating self-evaluation and enabling consistent advancement towards mastery, Studdy enhances student learning outcomes through the implementation of performance-based assignment adjustments.
Miro (Khusid, 2023) *Chatmind* (equipo Xmind, 2023)	Creation of concept maps with artificial intelligence	Proprietary model	Harnesses generative AI to create concept maps, diagrams and visual representations of knowledge and information, facilitating comprehension and retention for learners.	In educational and professional settings, the platform's capacity to support knowledge construction and accommodate user input to facilitate meaningful learning experiences is instrumental.

5.3 Discussion: Generative AI between Education 4.0 and 5.0

The case studies shown in Table 5 highlight the profound and systematic effects of generative AI in various educational fields. This demonstrates the adaptability of the technology in customizing learning experiences and enhancing results. Generative AI is transforming the way we approach education in numerous ways, including conversational AI models (e.g., ChatGPT-4o, ChatGPT 4, ChatGPT 3.5, Gemini, Claude3, Copilot, Cohere, POE, Groq, PERLEXITY, Reka, You), which dynamically adapt lessons to meet the unique learning needs of each user and platforms such as Duolingo and DreamBox, which offer personalized support and guidance. These platforms exhibit noteworthy success indicators, such as heightened user involvement, enhanced academic performance and improved proficiency growth, thereby underscoring the effectiveness of personalized AI. Moreover, learning outcomes are further improved as platforms such as Italki and ASSISTments utilize generative AI to provide individualized tutoring and immediate feedback. Platforms serving as personal assistants for educators, such as School AI and MagicSchool, optimize administrative duties, thereby enhancing educators' support and productivity. By integrating generative AI into the interfaces of chatbots, platforms such as Explainpaper and ChatPDF improve the accessibility and engagement of educational materials. In addition, online learning platforms such as Socratic and Studdy facilitate personalized learning experiences by offering adaptive feedback and assistance with assignment correction.

In generating visual representations of knowledge and concept maps, generative AI applications such as Chatmind and Miro exemplify the transformative potential of AI. These platforms facilitate the comprehension and retention of complex concepts by allowing users to create visually captivating and informative diagrams through the utilization of sophisticated algorithms. In general, the aforementioned case studies serve as prime examples of how generative AI can transform the field of education through the provision of interactive, progressive and personalized learning experiences that cater to the varied requirements of both students and instructors.

This section showcases case studies that demonstrate the profound potential impact of generative AI on adaptive learning. These findings are consistent with the progression from Education 4.0 (Brandl & Schrader, 2024) to Education 5.0 (Shanto et al., 2024). Education 5.0 expands personalization to encompass social and emotional learning, critical thinking and the promotion of human connection, whereas Education 4.0 accentuates the integration of sophisticated digital technologies to individualize learning experiences (Shanto et al., 2024).

Within the framework of Education 4.0, generative AI is effectively implemented on platforms such as Knewton and Duolingo to customize resources and content according to each learner’s specific requirements. These platforms facilitate personalized recommendations and dynamically adapt to the difficulty of lessons, thereby promoting increased student engagement and expediting the development of skills. Similarly, DreamBox and ASSISTments adhere to the tenets of Education 4.0 by providing personalized guidance and immediate intervention through the use of generative AI-powered real-time feedback.

With the advent of Education 5.0, there is an increased emphasis on social and emotional learning, as exemplified by platforms such as SchoolAI and MagicSchool. These platforms facilitate human interaction and emotional support among students while also operating as personal assistants for instructors, optimizing administrative duties and increasing output. In addition, generative AI applications such as Explainpaper and ChatPDF integrate conversational interfaces with educational materials, thereby increasing engagement and accessibility under the tenets of Education 5.0.

At the intersection of Education 4.0 and 5.0, platforms such as Socratic and Studdy offer adaptive feedback and AI-powered assignment correction. Through the dynamic modification of assignment and intervention levels in response to student performance data, these platforms facilitate individualized learning encounters that maximize student comprehension and engagement. Moreover, following the tenets of Education 5.0, generative AI applications such as Chatmind and Miro facilitate the visual depiction of knowledge and concept mapping, thereby promoting collaborative learning environments.

As stated in the conclusion, the case studies illustrate how generative AI supports the paradigms of Education 4.0 and 5.0 by providing socially embedded, personalized and adaptive learning experiences. By combining sophisticated technology with human oversight, these platforms establish a pathway towards an educational future that is characterized by individualized instruction, comprehensive growth and continuous knowledge acquisition.

6 Challenges and Concerns

As we contemplate the auspicious prospect of incorporating generative AI into personalized and adaptive learning, we must adopt an impartial standpoint when examining this innovation. Although the prospective advantages are profound, educators, technologists and stakeholders must confront substantial obstacles and apprehensions. These challenges highlight the intricacies that arise when integrating sophisticated technology with the complex realm of education, ranging from ethical quandaries regarding data utilization to pedagogical implications regarding the human element. This section examines the numerous concerns and challenges that arise when generative AI and education are combined.

6.1 Ethical concerns

There are numerous transformative possibilities associated with the implementation of generative AI in education. The increasing technological sophistication of classrooms and curricula raises significant concerns regarding the ethical implications of these advancements. There are distinct ethical considerations that educators, developers and policymakers must conscientiously confront in light of the convergence of machine learning, data analytics and educational methods.

A. Data privacy and security

An inevitable consequence of the growing dependence on AI-powered educational platforms is an escalation in the volume of data gathered. Each pupil's engagement, response, interaction and contact can be monitored, analysed and processed. Although this information is of great value in terms of adapting and customizing educational experiences, it also gives rise to urgent issues regarding the privacy of students (Zohny et al., 2023).

- **Data storage:** It is imperative to encrypt all sensitive data during transmission and storage to safeguard it against unwanted access and security breaches. It is advisable to utilize secure storage solutions, which may include cloud-based storage that incorporates robust security measures such as multi-factor authentication and frequent security audits.
- **Access control:** Data access should be tightly controlled, ensuring that only authorized individuals are granted access. Implementing role-based access control (RBAC) facilitates the management of data access permissions based on predefined roles (Zhou et al., 2013).
- **Data governance:** It is necessary to implement robust data governance structures that incorporate data reduction principles to prevent the collection of excessive or irrelevant information. It is important to regularly undertake privacy impact assessments to detect and address any concerns (Janssen et al., 2020).

B. Potential biases in AI-generated content

For training, AI models, especially generative ones, require enormous datasets. Frequently derived from pre-existing content, these datasets may contain historical or societal biases. There is a potential for AI-generated content to incorporate these biases when biased data are utilized for training AI models (Liebrenz et al., 2023). By way of example, if a historical dataset fails to adequately represent specific cultural or societal contributions, the artificial intelligence could generate content that reinforces these exclusions or distortions. This may result in biased educational resources that fail to provide an all-encompassing or unbiased perspective on various subjects. To tackle this issue, it is imperative to conduct thorough curation and evaluation of training data, in addition to routinely validating content generated by AI.

- **Training data curation:** It is essential to meticulously curate and evaluate the training data. It is important to make an effort to incorporate diverse and representative statistics that accurately depict the cultural and societal contributions of different groups (Chang & Jia, 2022).
- **Bias detection and mitigation:** Techniques and approaches to identify and minimize bias in AI models have to be developed and applied (Shrestha, Kafle, & Kanan, 2022). Periodic audits and fine-tuning of the algorithms can assist in guaranteeing impartiality.
- **Content validation:** The accuracy and impartiality of AI-generated material should be verified regularly to ensure that it presents a comprehensive and fair viewpoint on different topics. An integrated method that incorporates human instructors can be utilized to assess or enhance AI-generated materials.
- **Algorithmic transparency:** Enhance the transparency of AI models by offering explanations for AI judgments and allowing access to the underlying algorithms and data sources for examination (Hind et al., 2020).

6.2 Technical challenges

The undeniable potential of generative AI to revolutionize and improve the educational domain is immense. Nevertheless, the process of incorporating this cutting-edge technology into the field of education is fraught with technical obstacles that require scrupulous consideration. Not only do these obstacles ascertain the efficacy of AI in education, but they also establish its dependability and credibility.

A. Ensuring quality and accuracy of AI-generated content

The capacity of generative AI to autonomously generate immense quantities of content is its primary appeal. However, quality and precision should not be compromised in the pursuit of producing a large quantity of content (Stahl & Eke, 2024). Misconceptions, erroneous learning and a diminished level of confidence in the platform are all consequences that may result from misinformation or inaccurately produced content in an educational setting (Johri et al., 2023). A formidable obstacle exists in guaranteeing the precision, pertinence and pedagogical integrity of content produced by AI. Continuous validation, quality checks and frequently a hybrid approach involving human educators to evaluate or supplement AI-generated materials are imperative in this context.

- **Continuous validation:** Continual validation techniques should be employed to guarantee the precision, pertinence and educational integrity of AI-generated content. This can encompass both automatic inspections and manual evaluations conducted by educators.
- **Quality checks:** Regular quality checks should be conducted to identify and rectify any inconsistencies in the produced content. These tests may involve comparing AI-generated information with established educational standards and benchmarks.
- **Hybrid approach:** A combination of human educators and AI-generated resources should be utilized, with the human educators reviewing and enhancing the materials to ensure that they adhere to educational standards and offer a thorough understanding of the subject matter.

B. Overfitting and generalization in AI models

The balance between overfitting and generalization is one of the fundamental challenges in machine learning and AI. Overfitting occurs when an AI model becomes overly tailored to its training data, performing admirably but failing to generalize to new, previously unseen data. In an educational context, this could mean that an AI system, after being trained on a specific curriculum, might struggle to adapt to new educational materials or diverse student interactions outside its training set (Patton et al., 2023). Addressing this challenge requires robust model training methods, validation techniques and regular model updates based on real-world feedback and data.

- **Robust model training methods:** Employ resilient model training procedures that incorporate techniques such as cross-validation (Berrar, 2019) and regularization (Poggio, Torre, & Koch, 1987) to mitigate overfitting and ensure the ability to generalize effectively to novel data.
- **Validation techniques:** Employ validation approaches that entail evaluating the model on varied and representative datasets to guarantee its optimal performance across multiple scenarios and student interactions.
- **Regular model updates:** Continuously update models with real-world input and fresh data to guarantee their ongoing relevance and efficacy. This can entail utilization of iterative learning methods, in which the model is regularly updated and refined with fresh data.

6.3 Pedagogical concerns

The marriage of generative AI and education holds significant promise for transforming teaching and learning. However, this union also brings forth a set of pedagogical concerns that delve into the essence of the teaching and learning process. These concerns revolve around the human aspect of education and how AI integration might affect it (Alasadi & Baiz, 2023).

A. Balancing AI-driven content with human touch

Education is more than the mere transfer of information; it is a deeply human process, enriched by interpersonal interactions, empathy and the unique insights that educators bring to the table. While generative AI can tailor content to individual learners, ensuring optimal difficulty levels and pacing, it cannot replicate the nuanced understanding, motivation and mentorship that human educators provide. The challenge lies in ensuring that AI-driven personalization enhances the learning experience without sidelining the irreplaceable human touch (Bankins, 2021). Integrating AI should not make education a purely transactional process but should serve to augment the rich tapestry of human interactions in the learning journey.

B. Making sure AI augments rather than replaces human educators

With the capabilities of AI growing exponentially, there is a looming concern about its role in the educational ecosystem. Will AI systems replace human educators? The pedagogical stance should be clear: AI is a tool, not a replacement. Human educators bring a depth of understanding, emotional intelligence and adaptability that AI cannot replicate (Alam, 2021). The goal should be to use AI to handle repetitive tasks, provide personalized content and offer insights based on data analytics, thereby freeing educators to focus on more in-depth teaching, fostering critical thinking and building meaningful relationships with students.

7 Discussion and future directions

The emergence of generative AI in education marks a quantum leap forward in our ability to reason about and perform teaching and learning tasks. Nevertheless, this new progress brings with it several complex issues relating to ethics, technology and teaching.

When generative AI and education come together, they create a lot of social problems. Top priorities include data protection, possible bias in AI-generated material and the finer points of academic honesty. Academic integrity concerns are raised in an environment where AI can generate new research topics, write articles and solve difficult problems. The ease with which students can access and utilize AI tools to complete their assignments gives rise to concerns regarding the precision and originality of their work. Regarding this emerging facet of academic ethics, imparting ethical conduct to students and devising methods to verify the precision of their work has become even more critical. Merely prohibiting the misuse of AI is insufficient; it must be employed to enhance the learning process rather than simply circumvent authentic academic labour.

From a technical standpoint, it is critical to ensure that content generated by AI is precise and trustworthy. Adaptation-wise, artificial intelligence is proficient, but it also has some flaws. Continuous model affirmation and refinement are required to prevent issues such as overfitting, which occurs when models perform well with historical data but struggle with novel data.

Using AI in the classroom must be approached with caution concerning instruction. Humans are the foundation of education. AI-driven data can provide customized insights and content, but they cannot replace the nuance, comprehension and direction that the human touch offers. The challenge is to ensure that these essential human qualities are not eclipsed by AI-driven progress. Furthermore, given its potential to assist with academic tasks, it is critical to unequivocally define the function of AI. AI should be a beneficial instrument that enhances learning without detracting from students' genuine efforts and development.

The move of generative AI into education is a trip full of both opportunities and problems. It is a long road that requires care, self-reflection and a strong dedication to the sacredness of education. Dealing with these problems together and with the student in mind can turn them into stepping stones that lead to a better learning experience for students all over the world.

There are a lot of exciting things that could happen with generative AI in the next few years and we talk about some of them in this part. Technology is changing fast and people are learning more about what teachers need (Bahroun et al., 2023). This means that artificial intelligence in education is constantly changing too. The way the material is provided, tests are given and personalized learning paths are put together will likely change when big discoveries happen soon. Ubiquitous learning is one potential option. In this method, learning environments are built into everyday life so that students can access relevant learning materials at any time and from anywhere. That is why educators (who know a lot about how to teach) and technologists (who use AI to meet those needs) need to work together to make this idea come true (Lim et al., 2023). Looking ahead, generative AI and education working together could lead to a time when learning is not only personalized but also a natural part of our everyday lives.

8 Conclusion

We examined generative AI and how it can be combined with adaptive personalized learning, showing the immense potential impact of the combination of these areas on the world. Answering RQ 1, we carefully looked at current uses of generative AI in flexible and personalized learning, showing a range of methods on different educational platforms. Through personalization and adaptability, the AI-based services that can be used in education (explained in Section 5) show how generative AI improves learning experiences.

Concerning RQ 2, we discussed the real benefits of using generative AI in schools. Examples presented in Section 5 show better results for students, higher levels of participation and faster skill growth. Concerning RQ 3, our comparison in Section 5 showed the changing of education and the potential of generative AI to bring about major changes. We presented the pros and cons of the progress of this technology by looking at both its successes and problems. Concerning RQ 4, we carefully analysed the problems and issues when using generative AI in school settings. For more information on ethics problems, technical limits and teaching issues, see Section 6. Lastly, we suggested some ideas about the future of generative AI and adaptable learning in Section 7, which was in response to RQ 5. For a world where learning is easily integrated into everyday life, we envisioned teachers and technologists working together.

Overall, we need to be very careful when integrating generative AI because we believe that education is on the verge of a huge transformation. We expect in the near future that learning will not be innovative but also open to everyone by balancing the amazing capabilities of AI with social concerns, technology limitations and best practices for teaching. Discussing Education 4.0 and Education 5.0 highlights the significance of personalized, publicly integrated learning experiences in defining the future of education.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

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