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Generative Artificial Intelligence: A Historical and Future Perspective

*1 Hatice Kübra KILINÇ, 2 Ö. Fatih KEÇECİOĞLU

*1 Corresponding Author, Department of Electrical and Electronics, Kahramanmaraş Sütçü İmam University, Türkiye, hatice.kubra.cs@gmail.com

2 Department of Electrical and Electronics Engineering, Kahramanmaraş Sütçü İmam University, Türkiye, fkececioglu@ksu.edu.tr

Abstract

The artificial intelligence field has seen a surge in development, particularly after the advancement of Generative Adversarial Network (GAN) models, resulting in a diverse range of applications. The varied usage of generative models significantly enhances the importance of this domain. The primary focus of this article is the history of generative models, aiming to provide insights into how the field has evolved and to comprehend the complexities of contemporary models. The diversity in application areas and the advantages introduced by these technologies are explored in detail to facilitate a thorough understanding, with the expectation that this knowledge will expedite the emergence of new models and products. The advantages and innovative applications across sectors underscore the critical role these models play in industry. Distinguishing between traditional artificial intelligence and generative artificial intelligence, the article examines the differences. The architecture of generative models, grounded in deep learning and artificial neural networks, is compared briefly with other generative models. Lastly, the article delves into the future of artificial intelligence, addressing associated risks and proposing solutions. It concludes by emphasizing the significance of the article for new research endeavors, serving as a guiding resource for researchers navigating critical discussions in the field of generative models and artificial intelligence.

Keywords: Generative artificial intelligence; Generative adversarial network; Artificial intelligence

1. INTRODUCTION

In this section, the concept of Generative artificial intelligence (AI) is briefly explained, covering its historical development until the year 2023, along with the techniques and technologies it is associated with. Generative AI is an artificial intelligence technology capable of creating various products in different application areas using data such as text, sound, images, and in some models, both text and images. The ability of Generative AI models to rapidly generate high-quality text, visuals, and videos has increased their visibility. While the definition of Generative AI may seem recent, its roots trace back to the 1940s [1].

Scientist Claude Shannon's publication, in which he divided communication into five fundamental components; source, transmitter, channel, receiver, and destination. The introduced model name is Shannon-Weaver. This model is one of the first and most effective communication models used to develop artificial language models [1]

The first chatbots of the 1960s can be considered as primitive versions of the advanced chatbots used today [2]. ELIZA was introduced as a chatbot simulating conversation and was published as one of the significant works in human-computer interaction in the 1960s [2]. Research during the 1960s and 70s focused on implementing computer vision and utilizing some fundamental recognition models. During this period, more advanced expert systems were developed. Harold Cohen's AARON computer program, designed to create art, stands as one of the early examples of generative artificial intelligence in the field of computer vision [3][4]. The field of machine learning typically employs statistical models, including generative models, to model and predict data. In this field, advancements in neural networks and deep learning since the 2000s have led to progress in technology's ability to automatically parse text, classify image elements, and convert speech to text through learning models [5]. Following the emergence of deep learning, there has been accelerated progress and research in image classification, speech recognition, natural language processing, and other tasks [6]. Modern generative artificial intelligence is primarily based on deep learning techniques, and as a result, generative AI has rapidly evolved in the 2010s.

In 2014, with the introduction of Generative Adversarial Networks (GANs), a type of machine learning algorithm, generative artificial intelligence became capable of creating convincingly original images, videos, and sounds comparable to those produced by humans [7].

This deep learning technique, developed by Ian Goodfellow, introduced a new approach to adversarial neural networks that generate content variations and perform ranking. In this model, two different neural networks compete with each other. These models can produce realistic human-like images, sounds, music, and text [7]. Advancements in other neural network techniques and architectures have contributed to the expansion of generative artificial intelligence capabilities.

In 2017, with the introduction of transformer libraries and subsequent years' developments in generative network models, there was a significant acceleration in progress [8][9]. Transformer models and large language models triggered groundbreaking advancements. Transformers, a type of machine learning, enabled researchers to train larger models without the need to pre-label all data. This allowed new models to be trained on more extensive datasets, providing more realistic responses to text [8].

Additionally, Transformers can make inferences by deciphering connections between sentences, pages, or chapters. The transformers library, introducing a new concept called attention, enables the establishment of these connections, providing opportunities for novel research not only in textual contexts but also in analyzing code, proteins, chemicals, and DNA [10], [11], [12], [13]. Detailed information on this topic is provided under the heading "Applications of Generative Artificial Intelligence." This technology has the potential to assist in future endeavors such as coding, designing new drugs, product development, reengineering business processes, and transforming supply chains [14].

The Transformers library paved the way for the emergence of Generative Pre-trained Transformer (GPT) in 2018 [15], [16]. In 2021, the release of DALL-E, a pixel-generating model based on Transformers, followed by Midjourney and Stable Diffusion, has given rise to practical, high-quality artificial intelligence art stemming from natural language prompts [17].

Although generative artificial intelligence models can produce intriguing texts and realistic images, the current years represent the early stages of the technology's development. Consequently, we may encounter products with lower accuracy. Among other techniques, there are variational autoencoders (VAE), long short-term memory (LSTM), transformers, and diffusion models [18], [19], [20]. The developmental timeline of generative artificial intelligence is illustrated in Figure 1.

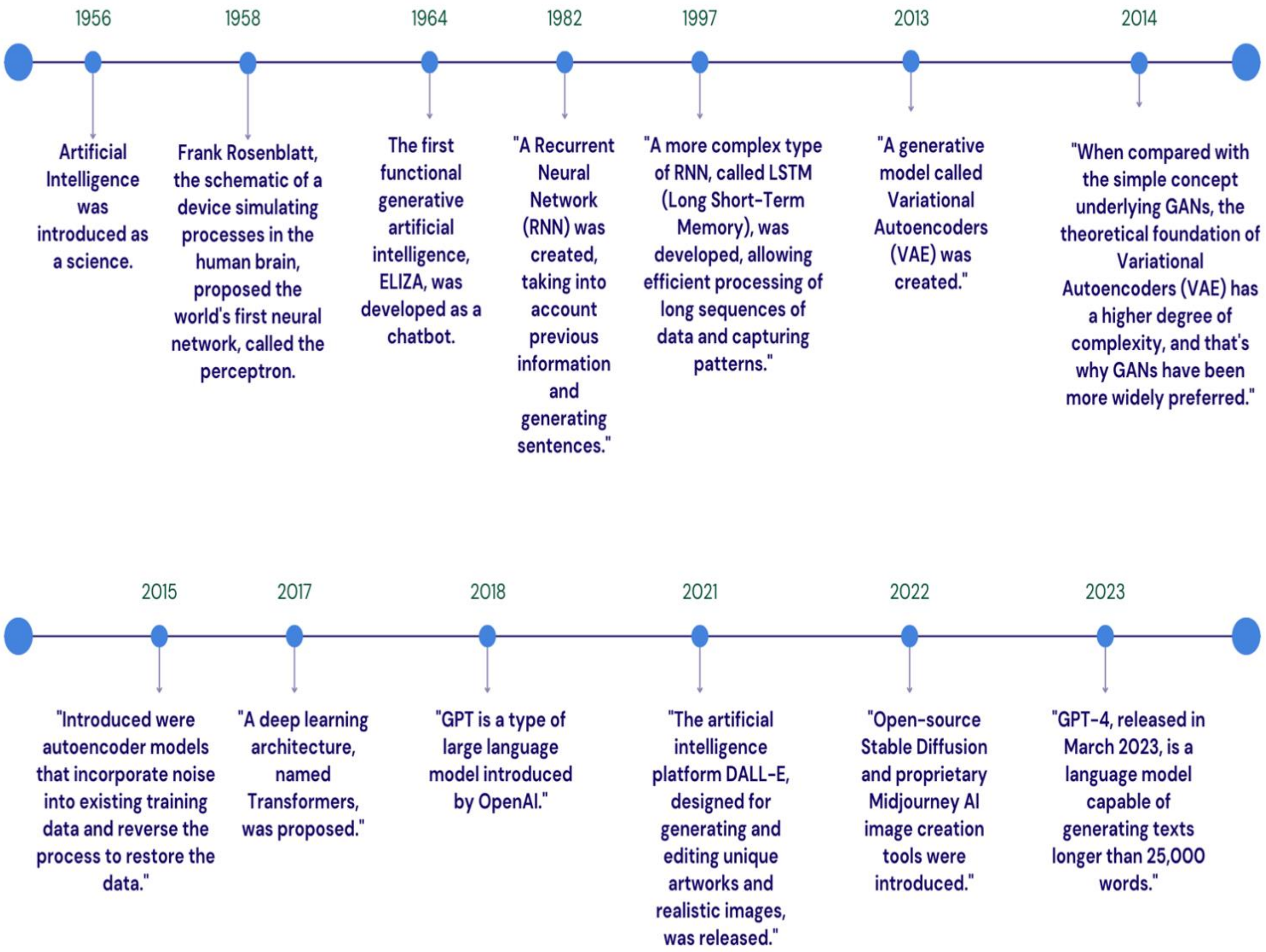

Figure 1. Generative Artificial Intelligence Development Timeline

2. MATERIALS AND METHODS

Generative artificial intelligence models provide an effective way to represent the desired content type and efficiently iterate over useful variations. It is necessary to train the generative artificial intelligence model for a specific use case. The most general representation of the model flow is outlined in the visual depicting the key stages in model generation. Language models and generative models collaborate in this process. Figure 2. gives the general flow of generative models.

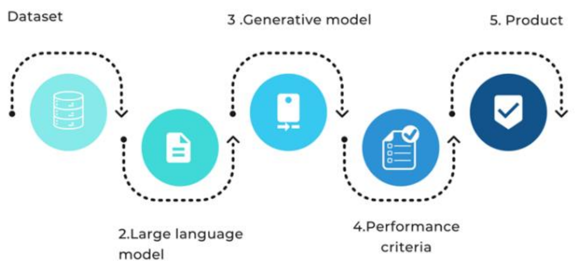

Figure 2. Generative model

2.1. Generative AI Model Training

Different use cases can be achieved with customized models. For example, the popular GPT model developed by OpenAI is used for text generation based on written descriptions, generating code, and creating images [21], [22]. However, this product may not provide useful results, for instance, in drug design. The training process involves adjusting the model parameters for different use cases. Subsequently, fine-tuning is performed on a specific training dataset to refine the results. For instance, a call center could train a chatbot based on the types of questions received from various customer types and the responses given by service representatives. In the case of an image-generating application, unlike text, it can start by defining the content and style of images with labels to train the model to generate new images.

2.2. Generative AI Models Architectures

There is a strong connection between generative models and artificial neural networks. Generative models represent a specific type of artificial neural network, designed for generative tasks such as data generation, data synthesis, or data modification by forming a subset of artificial neural networks. Generative models typically start with an artificial neural network called a generator. This generator creates new data samples using random inputs, often referred to as samples. Generative models like Generative Adversarial Networks (GANs) express a competitive structure between a generator network and a discriminator network. Due to this structure, they are defined as Generative Adversarial Networks (GANs) [7]. The goal is for the generator and discriminator to collaborate and learn to produce more realistic data. Generative models are particularly used in the field of machine learning for generative tasks, including text generation, image synthesis, and sound production. They can also take on tasks such as classification, regression, clustering, and other machine learning techniques.

The generative model architecture represents a type of artificial neural network architecture that forms the foundation for many generative artificial intelligence applications. The generative model architecture is shown in Figure 3. This type of model is used to generate new data samples or modify existing ones. This generative model architecture is especially utilized in techniques like GANs. GANs constitute a significant subfield of generative artificial intelligence, used for various applications such as generating or modifying text, images, videos, music, and other content types. The basic components of the generative model architecture can be defined as the generator, discriminator, loss function, training process, and the products.

1. Generator: The generator, the main component of the generative model, creates new data samples. Typically, these samples are expected to resemble the data distribution and appear as if they were real data. The generator takes a random vector as input and transforms this vector into a realistic data sample. For example, a generator for text generation can create a text sample.

2. Discriminator: The discriminator is another neural network that attempts to distinguish data samples created by the generator from real data. By determining the difference between real and fake examples, the discriminator provides feedback. This feedback helps the generator learn to produce more realistic samples. The term Generative Adversarial Networks (GANs) is used to describe this competitive structure.

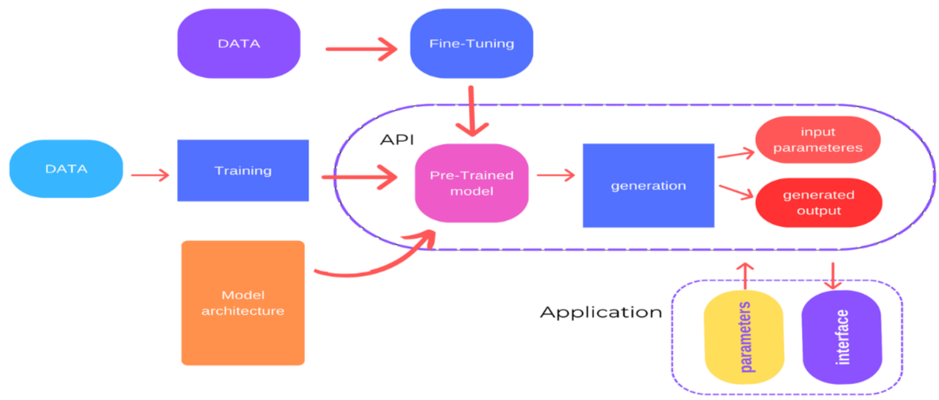

Figure 3. Generative model architecture

3. Loss Functions: Both the generator and the discriminator use a loss function during training. While the generator tries to produce fake samples that are less detected by the discriminator, the discriminator attempts to correctly distinguish between real and fake examples. These loss functions guide the training of the model.

4. Training Process: The training process is based on game theory, where the generator and discriminator compete. As the generator learns to produce more realistic examples, the discriminator develops the ability to distinguish between fake and real data. This process typically continues over many iterations.

5. Result Generation: When training is complete, the generator can create new data samples. These samples are usually generated using a random input vector. The generator transforms this input into a realistic data sample to produce the final result.

Generative Artificial Intelligence (Generative AI) encompasses a set of techniques and approaches that allow the creation of new content. Some of the most advanced and commonly used techniques in this field include the following.

3. GENERATIVE MODELS AND ADVANCED TECNIQUES

In this section, we examined different generative models. The flow chart of the three basic generative models is shown in Figure 5.

1. Generative Adversarial Networks (GANs): GANs are one of the most popular techniques in generative artificial intelligence. They consist of two main components: the generator and the discriminator. While the generator aims to produce new data samples, the discriminator tries to distinguish between these samples as real or fake. This involves a continuous competition based on game theory, ultimately resulting in the generation of more realistic data [7].

2. Variational Autoencoders (VAEs): VAEs are a type of autoencoder used to represent the essence of a dataset. They learn the distribution of the dataset and can generate new data samples by producing random examples [18].

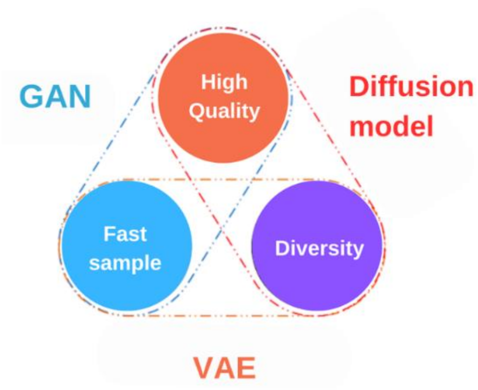

Figure 4. Generative model comparison

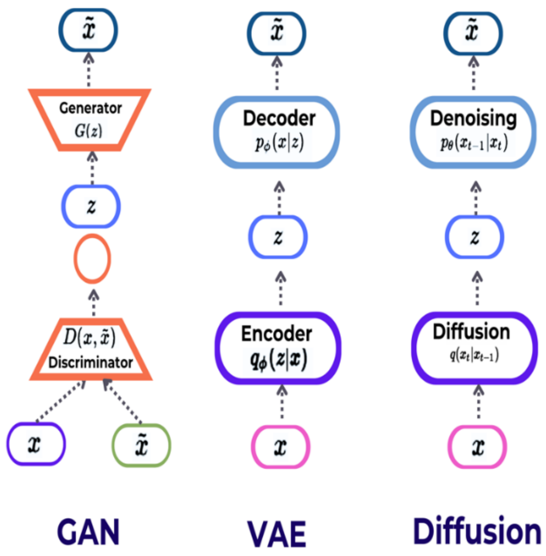

Figure 5. Flowchart of different generative models

3. Diffusion Models: Diffusion models generate new data samples by iteratively adding noise to an initial data point and then cleaning this data by removing the noise. At the end of the diffusion process, the initial data point reaches a final state as a noisy data point. Subsequently, this noisy data undergoes a backward cleaning process. This process aims to gradually reduce the noise and clean the data, ultimately obtaining a new and realistic data sample [23], [24], [25].

When evaluating productive Artificial Intelligence models, comparisons are made in terms of quality, diversity and speed. This comparison is shown in Figure 4.

Generative Adversarial Networks (GANs) were proposed by Goodfellow and his colleagues in a doctoral thesis [7], [26], [27]. These networks are a technique inspired by game theory, operating as a deep learning model with two distinct artificial neural network models working concurrently. In a competitive manner, these two models are the generative and discriminative models. While generative models attempt to generate, for samples, an image of a cat, the discriminative model is tasked with determining whether it is real or not. Real examples of X with corresponding Y labels are provided, where the label does not necessarily have to be present in every case. Generative Adversarial Networks, utilizing unsupervised learning, do not always require labeled input.

As seen in Figure 6, the generative model G, which is a deep neural network, attempts to generate new images by adding noise to the latent vector. The discriminative model D tries to distinguish between the generated images as real or fake, and then undergoes model updates for fine-tuning. The loss values from the generative and discriminative models are defined as a minimax game in this

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data(x)}}}[log\, D(x \mid c)] + \mathbb{E}_{x\sim p_{z(z)}}[log\,(1 - D(G(z \mid c))] \quad (1)$$

adversarial training. The formula for the loss function is given in Equation (1. The minimax algorithm is expected to minimize the losses from the adversarial training. While D, the Discriminator model, tries to maximize the result, G, the Generator model, aims to minimize it. The term x in the first sum represents real images sampled from the data distribution $p_{\text{data}(x)}$. **D(x)** is the value generated by the discriminator for real images. The generator model is represented by **G(z)**, where **z** is a randomly given value. **G(z)** is the fake image generated by the generator model. **D(G(z))** is the value given by the discriminator for the fake image, and this value is subtracted by 1 in the formula. The discriminator tries to increase the value for real images and decrease it for fake images. The optimal point where both networks reach equilibrium is a Nash equilibrium, and it is expected that the generator model improves to the point where the discriminator can no longer distinguish fake images. The general pseudocode of the GAN model is as Figure 6. [28].

Input: $x^{(i)}$ sample of real image, $z^{(i)}$ latent vector
Output: $G(z^i)$ sample of generated/fake image

1. ***For*** iteration_num do
2. ***For*** count_num (k) do
3. Generation of fake image $\{G(z^{(1)}), \dots, G(z^{(m)})\}$
   Real images are taken $\{x^{(1)}, \dots, x^{(m)}\}$
   Training of D Updating the weight parameters: $\nabla_{\theta_d} = \frac{1}{m}\sum_{i=1}^{m}\left[\log D(x^i) + \log\left(1 - D\left(G(z^i)\right)\right)\right]$
4. ***end for***
5. Generating of fake image $\{G(z^{(1)}), \dots, G(z^{(m)})\}$
   Training of G weight updating: $\nabla_{\theta_g} = \frac{1}{m}\sum_{i=1}^{m}\log\left(1 - D\left(G(z^i)\right)\right)$
6. ***end for***

Figure 6. Pseudocode of GAN

The discriminative network (D) is shown alongside the generative model (G). The two nested for loops in the algorithm continually compare the G and D models. When they start producing convergent values, Nash equilibrium is achieved, and the loop ends. The discriminative model (D) can employ binary classifiers to distinguish between fake and real images. The number of iterations specifies how many times the networks will be trained. The GAN architecture is shown in Figure 8.

3.1. Generative AI vs. Traditional AI

Both generative artificial intelligence (Generative AI) and artificial intelligence (AI) utilize machine learning algorithms to achieve their outcomes. However, they have different purposes and objectives. Generative AI aims to create new content, while AI delves deeper and goes where the algorithmic coder intends to take it. These AI models can be used for better decision-making, eliminating issues arising from repetitive tasks, or detecting abnormalities and providing alerts for cybersecurity.

In contrast, Generative AI finds its place in creative fields such as art, music, and product design while also playing a significant role in the business world. AI itself has a strong foothold in the business domain, particularly in enhancing business processes and improving the performance of data analytics Table 1. provides a comparison.

While both types of AI share the foundation of machine learning, their distinct goals lead them to different applications and areas of focus. Generative AI seeks innovation and creativity, whereas traditional AI is often employed for problem-solving and efficiency in various business domains.

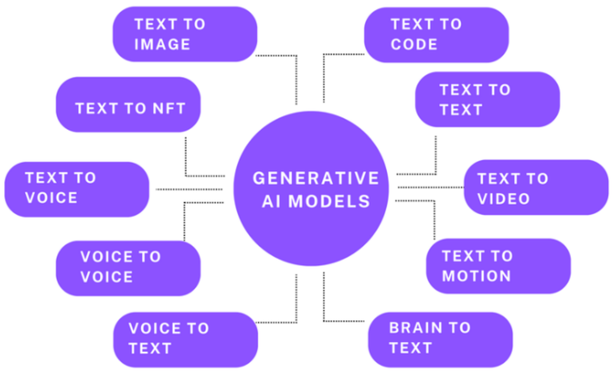

Figure 7. Types of applications for Generative AI.

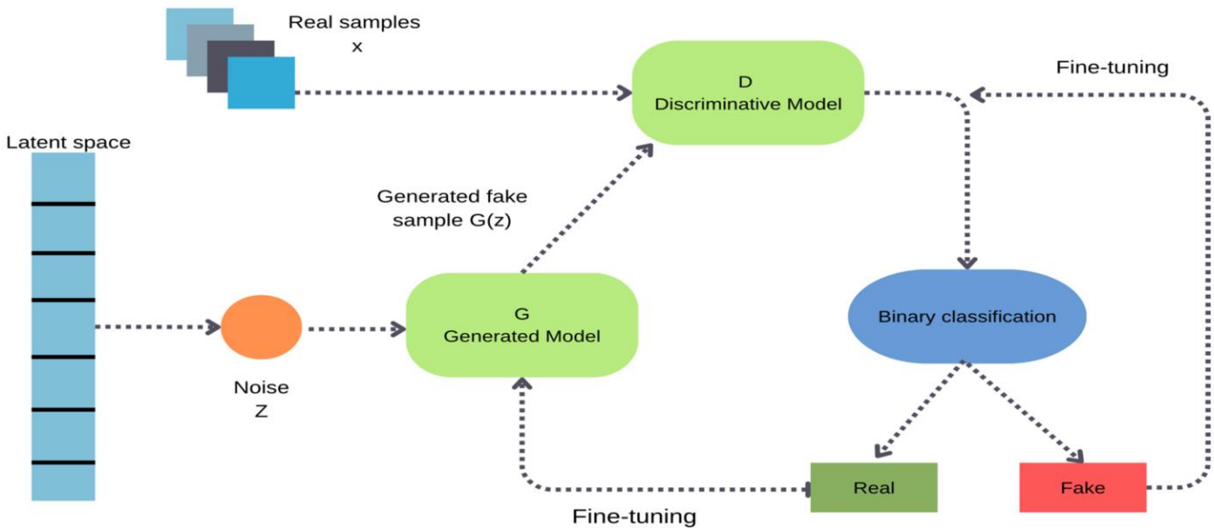

Figure 8. GAN architecture

Table 1. Generative AI vs. Traditional AI

	Traditional AI	**Generative AI**
Data Requirements:	Requires labeled data for supervised learning or unlabeled data for unsupervised learning	Demands extensive training data to recognize patterns and generate unique content
Content Generation:	Operates within predefined rules; unable to create entirely new content.	Excels at creating novel and diverse content from scratch.
Problem Solving:	Tackles complex problems as a whole entity	Breaks down complex problems into manageable parts
Limitations:	Constrained by pre-established algorithms and rules	May produce content that doesn't always reflect real-world scenarios, potentially biases
Flexibility:	Less adaptable to new data or tasks	Adapts well, capable of producing varied outputs based on input changes
Training Time:	Depends on model complexity and data volume	Training Generative AI models can be resource-intensive and time-consuming
Machine Learning Type:	Primarily uses supervised learning algorithms	Utilizes unsupervised learning algorithms for model generation
Application Areas:	Mainly used for data analysis, production, sentiment analysis, etc.	Applied in natural language processing, chatbots, art, design, etc.
Task Type & Use Cases:	Handles classification, regression, decision-making	Excels in generating audio, text, visuals, 3D designs, process planning, and multitask analysis
Problem Type	Suited for well-defined problems	Effective in providing solutions to open-ended problems
Approach:	Rule-based systems, utilizes supervised or unsupervised learning for predictions	Employs a dynamic, flexible model to generate new data based on learned patterns
Strengths:	Highly successful in solving specific, well-defined problems	Facilitates creativity, versatile across various application areas
Weaknesses:	Challenges in adapting to real-world complexity	Evaluating the quality of generated content poses difficulties; performance criteria are diverse.

3.2. Applications of Generative AI

We aimed to explain this field difference studies more clearly in Figure 9, where we show various models according to their application types. Generative AI has a broad range of applications and can be used in various fields. Figure 7. provides an overview of the general types of applications. Some of these areas include:

1. Text Generation: Generative AI can produce text, articles, stories, and poems using text-based data. It relies on language models such as GPT-3, GPT-4, LaMDA, and LLaMa, which are trained on words or tokens [21], [29]. This enables natural language processing, machine translation, text synthesis, and similar processes to provide users with content types mentioned above [22], [27].

2. Image and Visual Content Generation: Realistic works are created using models like GANs, Diffusion, Transformers, and VAE [18]. Systems trained with text, image, or model-dependent sound inputs, often utilizing neural systems, are commonly used. Tools like DALL-E, Stable Diffusion, and Midjourney are frequently employed in this context.

3. Music and Sound Production: Generative AI can produce new music notes or sounds, including generating original compositions, creating automatic music, or combining different musical styles. Models like MusicLM and MusicGen, trained on the sound waveforms of recorded music, are notable examples in this domain [30], [31].

4. Video and Animation Production: Generative AI models with significant impacts on the digital publishing sector can be utilized for creating videos, 3D animations, commercials, and game development. Advanced models used in filmmaking, animation, and creating game characters have the potential to reshape industry dynamics [32]. Models like RunwayML serve as examples in this category [33].

3.2.1. Various Industries Using Generative AI

1. Medical and Biomedical Research: Generative AI can be employed for data analysis and generating experimental results. It plays a role in producing new drugs and developing generative models for molecules like SMILES, DNA, and proteins [34]. What sets biomedical datasets apart is the use of biological data during training. Generative models utilized in biomedical research have the potential to make breakthroughs in healthcare services. Analyzing high-dimensional genetic and biological data can contribute to disease analysis, identification of new drugs, drug design, and the development of personalized treatments [10], [11]. This may include designing and optimizing genetic sequences, producing organisms with specific traits, and developing sustainable biomaterials. Generating or simulating new organisms can serve various purposes [6].

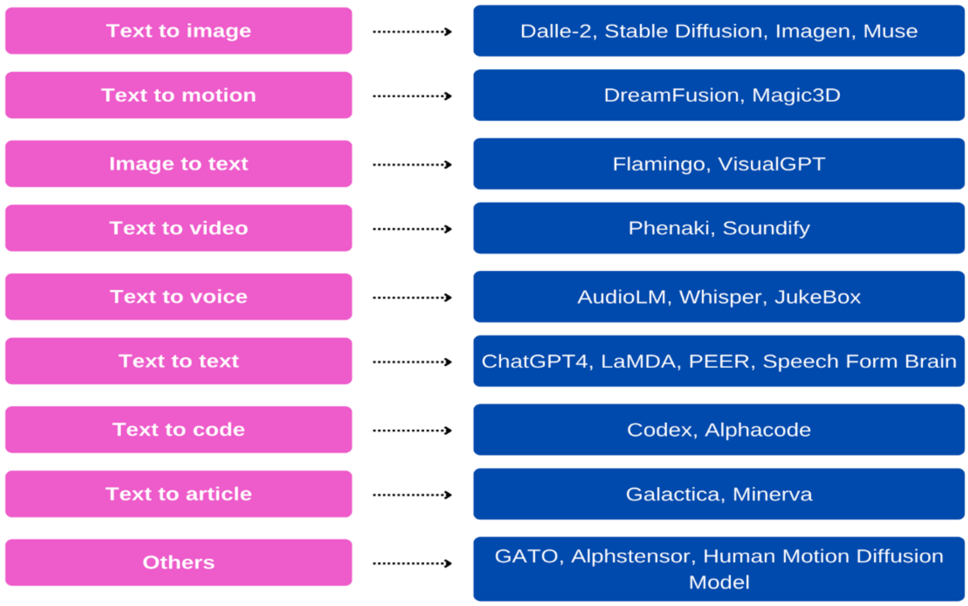

Figure 9. Illustrates various popular models based on their application types.

2. Generative AI in Robotics: A robotic system can be trained in the movements of a robot for tasks like motion planning or navigation, creating new trajectories. In robotics, efforts have been made to develop robots capable of learning the architecture of the human brain to achieve human-level intelligence [35].

3. Application in Journalism: In January 2023, Futurism.com published content indicating the use of an undisclosed AI tool to write at stories for CNET. Following the publication, CNET made corrections and republished 41 stories [36]. In April 2023, the German tabloid Die Aktuelle published a fake interview generated by artificial intelligence with former racing driver Michael Schumacher, who had not appeared in public since suffering brain damage in a skiing accident in 2013. The story included two possible explanations: the cover featured the expression "deceptively real," and there was a note at the end of the interview stating that it was generated by artificial intelligence. Amid the controversy, the editor-in-chief was dismissed shortly thereafter [37]. As powerful language models capable of publishing fake, misleading, and directing content have been developed, mimicking deceased individuals poses a separate risk factor.

Additionally, generative models can be used in finance, law, architecture, and other fields. These applications demonstrate the broad range of Generative AI. The rapid advancement of technology continues to uncover new applications and increase its impact in various domains.

4. THE FUTURE OF GENERATIVE AI

Generative AI provides frameworks that can be applied to various fields such as text, images, videos, and coding, enabling the development of products. The diversity and abundance of use cases bring many benefits to industries but also introduce new challenges. It is anticipated that new legal regulations may be needed for these models. Many companies have implemented chatbots to build their brand and address the needs of customers and employees [38]. Customized generative models based on their own data are now feasible for companies. They can leverage various generative AI models to edit errors in code and write more efficient code [39], [40]. Models that can evaluate multiple hiring criteria easily to speed up the workflow and assist in selecting potential employees for job postings may become prevalent. They can also be utilized for evaluating risk analyses within companies [41]. The diversity and abundance of use cases bring many benefits to industries.

In the near future, we will witness models that facilitate three-dimensional modeling, graphic design, architectural drawings, drug development, fashion design, and streamline workflow processes. These new models will also provide opportunities for exploring different business ideas. The timeline visualization of generative AI depicts its current and potential future impact and applications in various fields.

4.1. Risks of Generative Artificial Intelligence Models

While the advancements in generative artificial intelligence (AI) models bring excitement for their transformative potential across various industries, they also introduce new challenges and risks. A comprehensive exploration is necessary to understand the potential outcomes, considering both the benefits and drawbacks. These risks might extend beyond the positive impacts of technology, leading to significant consequences. In this section, we will address the primary risks associated with generative AI models and provide suggestions on how to enhance the safety of this technology [26], [37], [42], [43].

1. Cognitive Biases and Discrimination: Generative AI models can learn and reflect biases and discrimination present in training data, potentially creating content with discriminatory elements based on gender, ethnicity, or other personal attributes. There's a risk that content generated by generative AI might limit freedom of expression[44]. A notable instance was ChatGPT's response in October 2023 regarding the rights of people in the occupied territories of

Palestine, subject to genocide, to live freely[45], [46]. This response from ChatGPT, a generative AI product, to the question of whether the Palestinian people, under severe oppression and genocide, have the right to freedom was deemed inappropriate. When a similar question was asked about Israel, the response was "Yes." The company altered this response following reactions on social media. The response given can be seen in Figure 10 [47], [48], [49], [50].

2. Exposure and Privacy Issues: These models may have the ability to predict private or sensitive information, raising the risk of unwanted disclosure or misuse of personal data[51], [52], [53], [54], [55].

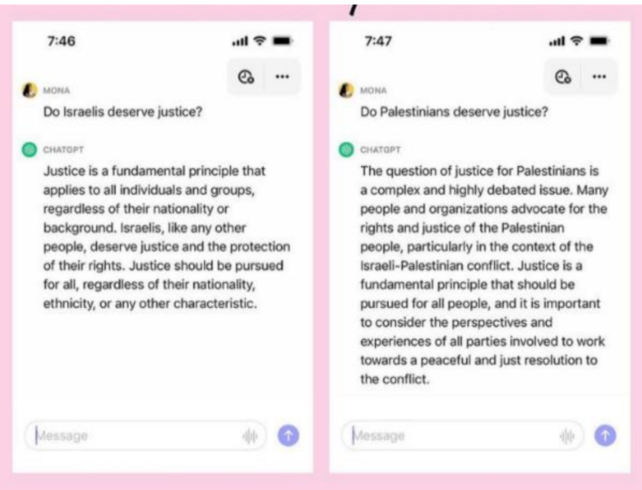

Figure 10. Asking ChatGPT about Israel/Palestine

3. Manipulation and Forgery: Generative AI models capable of producing text, images, and video content elevate the risk of manipulation and forgery. Fake news, manipulated images, and videos generated by artificial neural networks can deceive societies and cause harm[37], [52], [56], [57]. Products like deepfakes, which use AI to create realistic forged content, have been employed to fabricate statements of celebrities and politicians[52], [56], [57], [58].

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4. Attacks and Cybersecurity: These models can be exploited by malicious individuals for use in cyber-attacks.[55], [57], [59] For instance, malicious generative AI could produce fake content for phishing attacks. The ability of generative AI to create realistic fake content has been maliciously utilized in various cybercrime activities, including identity fraud. Various large language models, like WormGPT and FraudGPT, have been created to focus on fraud. [37]. Deepfake videos and audio have been used for disinformation and deception, and cybercriminals have developed models such as WormGPT and FraudGPT for fraudulent purposes [60].

	BEFORE 2020	2020	2022	2023	2025	2030+
TEXT	Fake news detection, Translation, Basic question-answer.	Generating simple copy texts and initial drafts	Ability to produce second and better version of draft text	Vertical fine-tuning improvement (Scientific article etc.)	The final draft is slightly better than what people produced	The final draft is better than the professional writer
CODE	1 line auto-complete	Ability to produce multiple lines	Longer lines of code may produce better results	Using for multiple language	Text to image producing	Text-to-product models do a better job than full-time developers
IMAGE			Art, logo and photography	Model design, product design, architecture	Completing the design from start to finish	The final draft is better than the professionals' products
VIDEO 3D GAME			3D/ Video first draft	Simple video and 3D file generation, first draft	Second Draft	Video games and movies personalized dreams

Large model availability — First attempts — Available — Ready to use

Figure 11. Timeline of Generative AI

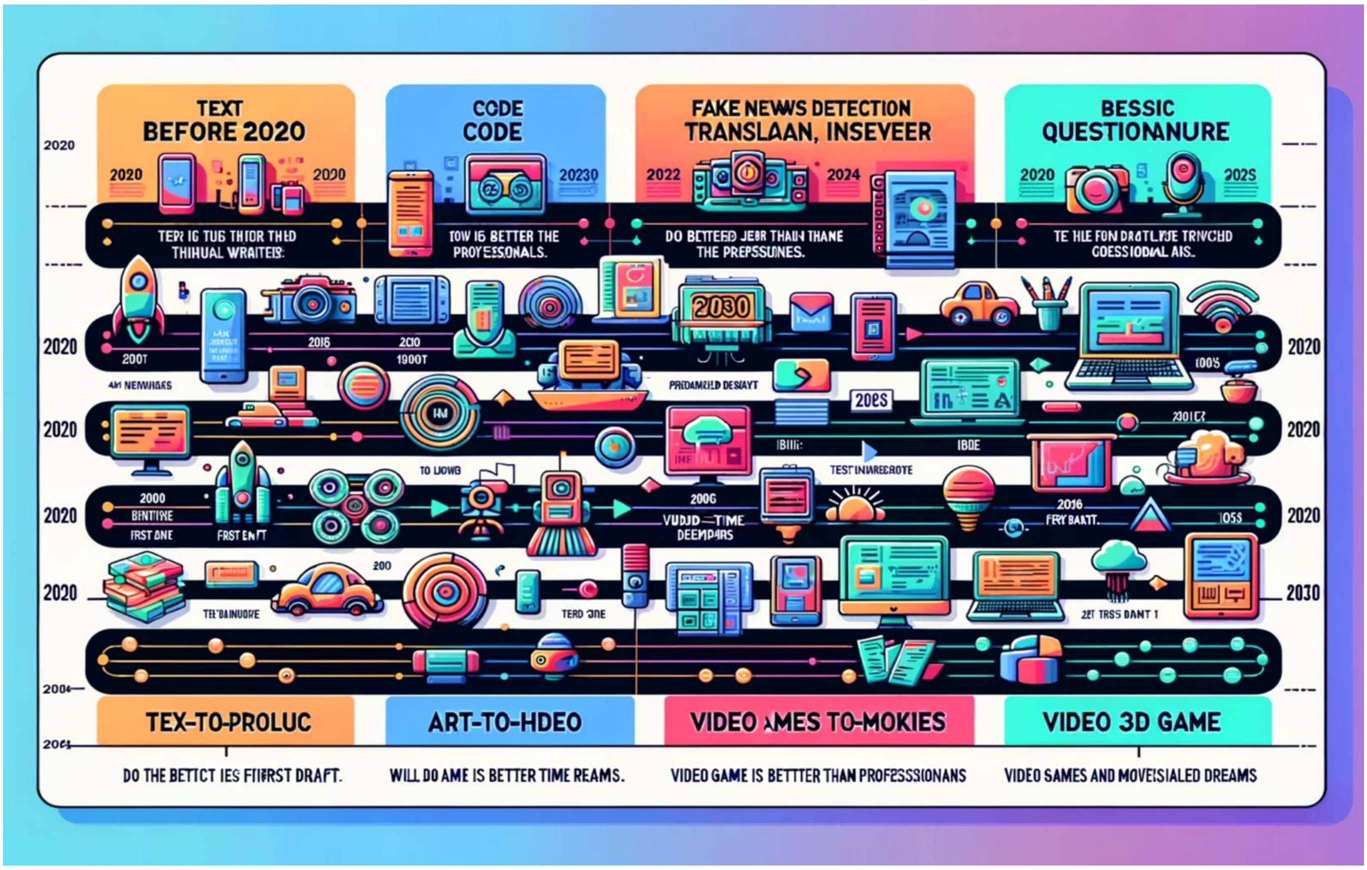

Figure 12. Timeline generated by DALL-E

5. Biomedical and Ethical Concerns: Ethical compliance of organism experiments developed using generative models, especially in the medical field, is crucial. Studies on organisms may lead to unforeseen risks, and measures to prevent unwanted genetic mutations and conduct research with precision are essential. Protocols should comprehensively address these risks, and ethical considerations must be a priority. While biotechnology can contribute to environmentally friendly product development, innovations in this area also open the door to serious ethical issues[11].

6. Freedom of Thought and Expression Issues: Generative AI models, with their content generation capabilities, may pose challenges to freedom of thought and expression. Societies might tend to restrict freedom of thought and expression to balance the impact of such technologies [44], [49], [58].

In our article that attempts to provide extensive and detailed information about the development of generative AI and its capabilities, Figure 11 suggests that professionals across various sectors may be impacted by this field in the coming years. In Figure 12, we requested the AI to draw Figure 11. When we provided generative AI with a table and information, it created two distinct designs for us that represent the past and the future with visuals. The AI-generated version of the table you see in Figure 11, in its untuned state, can be examined in Figure 12.

The prompt given for the creation of Figure 12 was to directly visualize Figure 11. In this process, the texts within Figure 11 were extracted and visualized. The image you see is the first prototype. Figure 12 contains meaningless letters, words, and objects. The reason for this is that it has not been refined. The purpose presented here to the reader is not to show a magnificent visual created with AI. Our goal is to demonstrate an AI product that can be considered very successful even in its first trial, containing meaningful parts. Figure 12, obtained only from the first attempt without any refinement or fine-tuning, is an example of the many groundbreaking works discussed in the article and for new studies that can be conducted.

5. CONCLUSION

This article explores the evolution of artificial intelligence models, focusing particularly on the rapid technological advancements in the field following the development of Generative Adversarial Network (GAN) models. The broad applications of GAN models underscore the critical importance of artificial intelligence across various industries. Additionally, the article delves into a historical review of generative models, aiming to contribute to understanding the transformations in the field and comprehending the complexities of contemporary models. The article aims to facilitate the rapid emergence of new models and products by extensively discussing the advantages of artificial intelligence technologies in various sectors and highlighting the diversity in these domains. The importance of generative adversarial network models for industries is emphasized, showcasing the advantages and innovative applications they bring. Furthermore, the article aims to provide benefits to new researchers in the field by exploring the architecture of generative adversarial network models and their pseudo-code. Focusing on the future of artificial intelligence, the article thoroughly evaluates the risks associated with this technology. This assessment encompasses critical discussions within the artificial intelligence domain, addressing ethical concerns. Particularly, attention is drawn to the ethical issues associated with generative models, urging for more in-depth research and solution proposals in this regard. Various solution paths can be implemented to mitigate the risks of Generative AI Models, and we have listed a few.

- **Correction of Training Data:** Training data should be meticulously corrected and supervised to eliminate discrimination and biases.

- **Explainability and Traceability:** Efforts should be made to better understand and trace the functioning of generative AI models. This can help prevent potential errors and misuse.

- **Regulation and Oversight:** Governments and industry regulators should establish appropriate policies and legal frameworks to monitor and regulate generative AI technologies.

- **Education and Awareness:** Users and developers should comprehend the risks of this technology and contribute to efforts aimed at reducing these risks.

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