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ADVANCED ARTIFICIAL INTELLIGENCE AND GENERATIVE MODELS: INNOVATIONS, APPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

INTELIGÊNCIA ARTIFICIAL AVANÇADA E MODELOS GENERATIVOS: INOVAÇÕES, APLICAÇÕES E DIREÇÕES FUTURAS DE PESQUISA

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Abstract
This paper gives a general discussion of recent advances in artificial intelligence generative models and their applications, future perspectives and limitations. The history pf AI and the development of the paradigms of automatic learning and deep learning through the development of powerful basic models such as large Language models, diffusion models and multi model’s systems. These technologies have demonstrated high potential in other fields for example health, education, engineering, software, industries, and scientific research. The drawbacks of these models are such as hallucinations, threats to privacy, biases interpret ability and high computational costs that make

Resumo
Este artigo apresenta uma discussão geral sobre os avanços recentes nos modelos generativos de inteligência artificial e suas aplicações, perspectivas futuras e limitações. A história da IA e o desenvolvimento dos paradigmas de aprendizado automático e aprendizado profundo, por meio do desenvolvimento de modelos básicos poderosos, como grandes modelos de linguagem, modelos de difusão e sistemas multimodais. Essas tecnologias têm demonstrado alto potencial em outros campos, como saúde, educação, engenharia, software, indústrias e pesquisa científica. As desvantagens desses modelos incluem alucinações, ameaças à privacidade, vieses de interpretabilidade e altos

them difficult to use widely. In this article, it is critically examining these limitations and more generally the ethical, social issues, legal and emphasises the imperative of responsible practices in AI for good governance and human regulation. Besides this study proposes a conceptual framework that involves AI innovation model architecture, risks, application domains and future research. It also identifies the most important trends in the part such as development of trustworthy and interpretable AI energy saving systems domains specific models and assessment procedures. Comprehensively this article offers an overview of the field of generative AI and presents valuable information on how to create reliable sustainable and human centered AI systems.

Keywords: Artificial Intelligence. Generative AI. Foundation Models. Large Language Models. Diffusion Models. Multimodal AI. Responsible AI. Explainable AI. Future Research.

custos computacionais, o que dificulta sua ampla utilização. Neste artigo, examinam-se criticamente essas limitações e, de forma mais geral, as questões éticas, sociais e legais, enfatizando a necessidade de práticas responsáveis em IA para uma boa governança e regulamentação humana. Além disso, este estudo propõe uma estrutura conceitual que envolve a arquitetura do modelo de inovação em IA, riscos, domínios de aplicação e pesquisas futuras. Ele também identifica as tendências mais importantes na área, tais como o desenvolvimento de IA confiável e interpretável, sistemas de economia de energia, modelos específicos para cada domínio e procedimentos de avaliação. De forma abrangente, este artigo oferece uma visão geral do campo da IA generativa e apresenta informações valiosas sobre como criar sistemas de IA confiáveis, sustentáveis e centrados no ser humano.

Palavras-chave: *Inteligência Artificial. IA Generativa. Modelos de Base. Modelos de Linguagem de Grande Porte. Modelos de Difusão. IA Multimodal. IA Responsável. IA Explicável. Pesquisas Futuras.*

1 INTRODUCTION

The evolution of Artificial Intelligence (AI) over the last few decades has seen a shift from symbolic, rule-based systems to data-driven, learning-based approaches (Mishra *et al*., 2025). In the mid-20th century, the initial AI systems were primarily based on rule-based programming and reasoning, which were not scalable or flexible in dealing with complex domains (Mundlamuri *et al*., 2025). Machine learning (ML) brought this paradigm change by allowing systems to learn patterns through data instead of explicit programming (Razzaq *et al*., 2025). Thereafter, the rise of deep learning, using multi-layered neural networks, has helped revolutionise the field, especially in computer vision, speech recognition, and natural language processing This evolution has been driven by a rapid increase in computational resources, access to large amounts of data, and improvements in optimisation algorithms (Torfi *et al*., 2020).

Generative models have experienced a booming growth in the field over the last few years, and they constitute a paradigm shift to the classical discriminative models

(Chakraborty et a., 2024). Where traditional models are trained to classify or predict, generative models seek to capture the distribution of the data and generate new data samples (Abukmeil *et al*., 2021). Original generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) have shown to generate realistic images and embeddings (Akkem *et al*., 2024). In recent years, transformers and diffusion models have pushed the boundaries of generative AI, allowing the generation of text, high resolution images, audio, video, and even scientific data. This has elevated generative AI to a cornerstone of contemporary AI research and practice (Bengesi *et al*., 2024).

One of the major factors that contributed to this change is the creation of foundation models and large language models (LLMs) (Chen *et al*., 2024). Foundation models are large pretrained models that are trained on large and diverse data, to be used for a variety of downstream tasks (Awais *et al*., 2025). LLMs, for instance, have shown impressive capabilities in language understanding and reasoning, code generation and conversational AI. Their transferability across tasks, together with approaches like fine-tuning and prompt engineering, has led to a higher degree of adaptability and scalability in AI applications. Additionally, their multimodal capabilities, which integrate text, vision and audio has broadened their application. Consequently, foundation models are increasingly seen as a unifying approach to building general AI systems (Karanikolas *et al*. 2023).

In spite of these developments, there are a number of serious issues, which indicate a significant research gap. The major problems with current generative models include hallucination, where the output can seem realistic but not factual; bias and fairness issues, which are caused by unbalanced or nonrepresentative training data; and lack of interpretability, which hinders adoption and use in high-stakes settings (Afreen *et al*., 2025). Moreover, because of the computational and environmental costs of training large-scale models, sustainability is also a concern (Wu *et al*., 2022). Their deployment is complicated by legal and ethical concerns, such as the privacy of data, intellectual property, and misuse (e.g., deepfakes and misinformation). Such constraints highlight the importance of the in-depth knowledge of the potentials and dangers of advanced generative AI systems (Shafik *et al*., 2025).

In this regard, the main aim of this paper is to carry out a systematic and comprehensive review of the latest innovations in artificial intelligence and generative models, their main applications, and the new direction of research. In particular, this paper focuses on: (i) discussing the history and taxonomy of generative models; (ii) analysing recent technical developments, like foundation models, multimodal systems, and agent-based AI; (iii) discussing the various real-world applications of generative models in fields such as healthcare, education, and scientific research; (iv) identifying important challenges and ethical concerns; and (v) suggested future research directions to create reliable,

First, it gives a coherent and organized overview of generative AI, combining the viewpoints of various model families and research directions. Second, it provides a detailed discussion of the most recent innovations, such as large language models, diffusion models, and multimodal architectures. Third, it offers a more detailed interpretation of applications and impact, with opportunities and limitations in different sectors. Fourth, it outlines key challenges and open research concerns, especially in the aspects of reliability, ethics, and scalability. Lastly, the article suggests a conceptual framework and research agenda in future studies that would inform the creation of next-generation generative AI systems.

2 THEORETICAL BACKGROUND

2.1 Artificial Intelligence and machine learning

Artificial Intelligence (AI) is the creation of computation systems that can execute functions normally performed by human intelligence, reasoning, perception, learning, and decision-making (Korteling *et al*.,2021). In the context of AI, a prominent paradigm has already become machine learning (ML), which allows systems to learn patterns and make predictions directly based on data. ML algorithms can be divided into supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Sarker *et al*., 2021). Supervised learning uses labeled data to learn inputoutput mappings, and unsupervised learning uncovers hidden structure in unlabeled data. Reinforcement learning, in its turn, deals with learning the best policies via the interaction with an environment (Yan *et al*., 2022).

Machine learning is effective because it can be used to generalize training data to new situations (Zhang *et al*., 2021). Conventional ML algorithms, including decision trees, support vector machines, and linear models, have been very successful in structured data environments (Tanveer *et al*., 2023). But they tend to work poorly with high-dimensional, unstructured data like images, audio, and natural language. The limitation has prompted the emergence of deep learning methods, which can automatically learn hierarchical features representations.

2.2 Deep learning foundations

Deep learning is a branch of machine learning and it is founded on the multilayer artificial neural network which is capable of modeling non-linear and complex relationships. These networks are based on the structure and workings of the human brain, as the neuron networks process and communicate information (Ahmed *et al*., 2023). Feedforward neural networks, convolutional neural networks (CNNs), recurring neural networks (RNNs), and most recently, transformers are key architectures in deep learning.

CNNs have shown great success in computer vision problems because they are able to extract spatial hierarchies in data, whereas RNNs and their derivatives (e.g., LSTM and GRU) have been extensively applied to sequential data processing (Bhatt *et al*., 2021). But the transformer architecture has transformed deep learning, particularly natural language processing. Transformers are based on self-attention to capture long-range dependencies, which provides parallel and better scalability than recurrent models (Huang *et al*., 2023).

The three factors that have a close relation with the success of deep learning include: (i) large-scale datasets, (ii) improvements in computational hardware like GPUs and TPUs, and (iii) better training methods like optimization algorithms and regularization methods. Such developments have made it possible to train larger and more complicated models and have led to the current generative AI systems (Shen *et al*., 2024).

2.3 Generative modeling

Generative modeling is concerned with training the probability distribution of data to produce new samples similar to the original data (Ruthotto *et al*., 2021). Mathematically, a generative model, based on data X, tries to learn the distribution P(X) or the conditional distribution P(X|Z), where Z are latent variables. This is opposite to discriminative models, which are learned to predict tasks based on decision boundaries or conditional probability P(Y|X) (Abukmeil *et al*., 2021).

There are various categories of generative models suggested in the literature. Variational Autoencoders (VAEs) are probabilistic encoders and decoders that learn latent representations to facilitate controlled data-generation (Girin *et al*.,2022). Generative Adversarial Networks (GANs) are two components: a generator and a discriminator, which are trained to play a minimax game, generating highly real synthetic data (Mohebbi Moghaddam*et al*., 2023). More recently, diffusion models have become popular, with the data generation process being represented as a sequence of denoising steps, and reaching state-of-the-art performance in image and video synthesis (Xing*et al*., 2024).

Simultaneously, parallel versions, especially transformer-based ones, have shown outstanding performance in sequence generation tasks (Katharopoulos *et al*., 2020). These models produce data tokens one at a time and they encode the intricate relationships in the data. Combining these strategies has greatly broadened the capabilities of generative modelling, allowing it to be used in text, images, audio, and multimodal information (Spathis *et al*.,2024).

2.4 Foundation models and scaling laws

Foundation models represent a paradigm shift in AI, where large models are pretrained with massive and diverse data sets and then adapted to a wide range of tasks (Chen *et al*., 2024). Unlike traditional task-specific models, foundation models provide a general backbone that can be fine-tuned or prompted for a variety of tasks, including language comprehension, image generation, and multi-modality reasoning (Sun *et al*., 2025).

One of the reasons for the success of foundation models is scaling laws, which describe the improvement in model performance as a function of model size, data size and computing power in a predictable way (Subramanian *et al*., 2023). In practice, it has been found that larger models trained with more data are more likely to achieve better performance and to acquire new skills, also referred to as emergent skills (Berti *et al*, 2025).

Moreover, recent studies highlight the role of the lifecycle of foundation models, which involves pretraining, fine-tuning, deployment, and ongoing adaptation (Schneider *et al*., 2024). This lifecycle approach emphasises issues pertaining to data quality, model alignment, model robustness, and ethics in the development process (Xu*et al*., 2025). As the scaling has been leading to impressive advances, it has also raised issues of computational cost, environmental footprint, and accessibility, and more efficient and sustainable methods should be researched. The theoretical basis of modern generative AI systems is foundation models, which are supported by scaling laws and lifecycle-based development, providing a common language to further the development of artificial intelligence in various fields (Pilot*et al*., 2025).

3 MAJOR CATEGORIES OF GENERATIVE MODELS

Generative models represent a basic type of machine learning methodology aimed at training on the underlying data distribution and generating novel data samples, which resemble the training data (Namiot *et al*., 2022). In the last ten years, deep learning has seen swift progress which has resulted in the development of a few strong generative modelling paradigms. The architectures, learning processes, and areas of application vary between these models, but they all make up the foundations of modern generative artificial intelligence systems (Regenwetter*et al*., 2022).

Recent surveys of research consistently point to Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), autoregressive models, transformer-based models, diffusion models, and multimodal generative systems as the main families that are driving innovation in generative AI. All categories have distinct advantages in terms of data fidelity, scalability, interpretability and versatility (Bengesi *et al*., 2024).

Table 1

Comparison of Major Generative Models

Model Type	Core Idea	Strengths	Limitations	Typical Applications
GANs (Generative Adversarial Networks)	Generator vs Discriminator (minimax game)	High-quality image generation	Training instability, mode collapse	Image synthesis, style transfer
VAEs (Variational Autoencoders)	Probabilistic latent representation	Stable training, interpretable latent space	Lower output quality than GANs	Data compression, anomaly detection
Autoregressive Models	Predict next token sequentially	Strong sequential modelling	Slow generation	Text generation, speech modelling
Transformers / LLMs	Attention-based sequence modelling	Scalability, generalization, reasoning	High computational cost, hallucination	NLP, code generation, chatbots
Diffusion Models	Iterative noise removal process	High-quality images, stable training	Slow inference	Image/video generation
Multimodal Models	Combine text, image, audio	Cross-domain reasoning	Complex training, alignment issues	Vision-language tasks, assistants

3.1 Generative Adversarial Networks (GANs)

One of the most significant advances in generative modelling is the introduction of Generative Adversarial Networks (GANs), which was introduced by Goodfellow *et al*. (Goodfellow *et al*., 2020). GANs are composed of a generator and a discriminator that are trained together in a minimax game. The goal of the generator is to generate realistic synthetic data, and the discriminator is judged on whether a certain sample is a real or a generated one (Jin *et al*., 2020).

The training process of adversarial training allows GANs to produce outputs that are very realistic, especially in image synthesis, video generation and style transfer. Such variants as DCGAN, StyleGAN, and CycleGAN have provided a much better quality and controllability of images. GANs are characterized by a number of challenges such as training instability, mode collapse, and convergence challenges, which restrict their applicability in some applications. Nevertheless, GANs are still popular in the creative sector, data augmentation, and simulation tasks (Liu *et al*., 2021).

3.2 Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) are probabilistic generative models that are trained in an encoder-decoder framework to learn a latent representation of input data. VAEs, unlike standard autoencoders, place a probabilistic model in the latent space, with a normal distribution of the latent space, which is usually a Gaussian prior distribution (Vishnu Shankar *et al*., 2025).

The encoder is used to decode the input into a latent distribution and the decoder is used to decode the data based on the sampled latent variables. With this formulation, VAEs can produce new data by sampling the latent space.

VAEs are especially appreciated due to their stable training program, interpretability, and easy latent space, which would be appropriate in applications like image creation, anomaly detection, and representation learning. Nevertheless, VAEs tend to generate more blurry results than GANs and diffusion models, and this restricts their applicability to high-fidelity generation tasks (Shrivastava *et al*., 2024).

3.3 Autoregressive models

Autoregressive models are used to produce data sequentially by modeling the conditional probability of each element given the other elements. They formally consider the joint distribution to be a product of conditional probabilities (Regis *et al*., 2022).

These models have been very successful in fields like natural language processing, speech synthesis, and forecasting time-series. Some of the most prominent include PixelRNN, PixelCNN, and early language models like GPT and RNN-based models (Liang *et al*., 2024).

The benefits of autoregressive models include the ability to estimate a likelihood precisely, and the ability to train stably, although generation is slow since they are sequential. This drawback is important when generating data of high dimensions, such as images and videos.

3.4 Transformer-based models

Models that are based on transformers signify a paradigm shift in generative AI, with the introduction of the self-attention mechanism. Transformers are able to handle long-range dependencies and process data in parallel unlike recurrent architectures (Luo *et al*., 2023).

Large-scale transformer models, especially Large Language Models (LLMs) like GPT, BERT (bidirectional), and their successors, have demonstrated impressive text-generation, reasoning, and knowledge-representation abilities (Raiaan *et al*., 2024).

Transformers are also now extended to text to vision (Vision Transformers), audio, and multimodal problems and are very versatile. They have such strengths as scalability, contextual interpretation, and adaptability, but have enormous demands in terms of computational resources and large-scale data sets (Khan *et al*., 2022).

3.5 Diffusion models

In recent times, diffusion models have become one of the most popular generative models, especially in image and video generation. These models work by gradually introducing noise to data in a forward direction and learning to reverse the process to create more samples (Xing *et al*., 2024).

The most important benefit of diffusion models is that they generate high-quality, varied, and stable images, frequently being more visually faithful than GANs. Notable examples are DDPM (Denoising Diffusion Probabilistic Models), Stable Diffusion and DALL·E-type structures (Croitoru *et al*.,2023).

Diffusion models are computationally costly and can be computationally inefficient, despite their success, as they involve many iterative steps during generation. Current studies are working on sampling faster and increasing scalability (Yang *et al*., 2023).

3.6 Multimodal generative models

Multimodal generative models build on the existing paradigms with the addition of multiple modalities of data that include text, images, audio, and video and combine them into a single system. These models seek to comprehend and produce content in various modalities at the same time (Balkrishna Rasiklal *et al*., 2024).

Most recent innovations feature models that can be trained to generate text-to-image, image-to-text, video-to-text, and cross-modal retrieval, and are applicable to virtual assistants, creative design environments, and human-computer interaction systems (Żelaszczyk *et al*., 2024).

Multimodal models use architectures, including transformers and diffusion-based models, typically with large-scale pretraining. They are very powerful but they present the challenge of alignment, data heterogeneity, and the complexity of evaluation (Mai *et al*., 2024).

The market of generative models is full of diverse models, each having its own advantages and constraints. The models GANs are more realistic and VAEs are more faithful to probabilistic modelling, autoregressive models are more efficient in generating sequential data, transformers are more scalable and generalisable, diffusion models are more high-fidelity, and multimodal systems are more integrative across domains. These model families, collectively, are the building blocks of modern generative AI, leading to innovations in research and practical implementation, as well as defining the future of artificial intelligence (Rahman *et al*., 2025).

4 KEY INNOVATIONS IN ADVANCED AI AND GENERATIVE MODELS

Artificial intelligence has experienced an unusually rapid evolution in the recent years, and this was brought about by a series of the associated advances in the architecture of models, training algorithms, and the design of systems. Most recent advances in generative AI are not due to a single breakthrough but a fusion of various different paradigms that address the shortcomings of the earlier models. The section describes the most influential innovations that shaped present systems of generative AI.

4.1 Large Language Models

Large Language Models (LLM) is one of the most significant developments in artificial intelligence. These systems are trained with large text volumes, using transformer architectures, to learn linguistic patterns, contextual relations and semantic structures (Chaitanya *et al*., 2024). Unlike earlier natural language processing models, LLMs are capable of a wide range of tasks, including text generation, summarization, translation, reasoning, and code generation, without training on the specific task (Min *et al*., 2023).

The ability to generalize across domains with techniques such as in-context learning and prompt engineering is one of the most important properties of LLMs. This flexibility makes them acquire new tasks with minimum supervision. Moreover, recent developments have enhanced their reasoning powers enabling them to resolve complex issues with chain-of-thought prompting and refinement. Despite such benefits, the biggest challenges that remain the subject of study include the hallucination, bias, and the cost of the computation (Basiouni *et al*., 2025).

4.2 Vision-Language Models

Vision-Language Models (VLMs) extend the capabilities of LLMs by including both visual and textual information in the same model. They learn to produce joint image and text representations, and can be applied to image captioning, visual question answering, and text-to-image generation (Ghosh *et al*., 2024).

Advances in multimodal learning have led to paradigms that can not only interpret images, but to also make contextual reasoning regarding images. An example is that complex visual images can be decoded into a form of description or instructions by the system through the input of images. It is perception-language integration, and one of the ways to more general and more human-like AI systems. However, a significant challenge is to make modalities robust and aligned (Bordes *et al*., 2024).

4.3 Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG) solves one of the inherent weaknesses of generative models, namely their use of fixed training data. Traditional LLMs implicitly encode knowledge in model parameters and this may result in outdated or wrong information. RAG is able to address this limitation by integrating generative models with external knowledge retrieval systems (Gupta *et al*., 2024).

In a classic RAG system, data pertaining to the generation is obtained by searching external databases or document archives and fed into the generation process. The method enhances the level of factual accuracy, interpretability, and the ability to adapt to the domain-specific tasks (Han *et al*., 2024). It finds its special use in such applications as question answering, legal analysis and enterprise knowledge systems where it is necessary to have the latest and verifiable information. However, there are still issues related to maximizing the quality of retrieval, minimizing latency, and consistency in the retrieved content and the produced outputs (Yang *et al*., 2024).

4.4 AI agents and tool-using models

The other noteworthy innovation is the introduction of AI agents, which further expands generative models from passive respondents to actively resolving problems. AI agents are capable of planning, reasoning, and communicating with external tools, situations, and APIs to accomplish intricate tasks, in contrast to autonomous models. They usually have LLMs along with other things like memory, planning modules, and processing frameworks. (Boussioux *et al*., 2024).

AI systems are helped by models that can use tools to do things like search the web, run code, analyse data, and make decisions. This is a big step forward for AI systems that can work on their own since it changes how they interact from static to dynamic. But it also brings up new problems with reliability, safety, and control, particularly in real-world or high-stakes situations (Qin *et al*., 2024).

4.5 Efficient and small language models

Although large-scale models have shown remarkable performance, their scaling and accessibility have been questioned due to their heavy computational and energy demands. Consequently, interest in efficient and small language models with the potential to achieve competitive performance using less resources has increased (Wang *et al*., 2020).

Methods like model compression, knowledge distillation, quantization, and sparse architectures have been proposed to overcome these challenges. Smaller models are especially useful to be deployed in resource-constrained environments, including mobile devices and edge computing systems. Moreover, they help make AI more sustainable through energy consumption and carbon footprint. The question of efficiency vs. performance is a dynamic field of research (Li *et al*., 2023).

4.6 Synthetic data generation

One of the most impactful uses of generative models has been synthetic data generation, which allows the generation of artificial data sets that are similar to real-world data distributions. This is particularly effective in the cases that involve limited, sensitive, or costly data, e.g., healthcare, finances, and autonomous driving (Lu *et al*., 2023).

The generative models are able to generate high quality synthetics data that can be utilized to train and test as well as validate models to enhance model robustness and generalization. Furthermore, synthetic data will improve privacy issues by minimizing the use of actual user data. Nevertheless, it is paramount that synthetic datasets are realistic, diverse, and equitable, since poorly generated datasets may lead to biases or deteriorate the performance of the models (Rusum *et al*., 2023).

4.7 Human-AI collaboration

A notable shift in recent AI research is the focus on human-AI collaboration, where generative models are designed to augment rather than replace human capabilities.

In this paradigm, AI systems act as intelligent assistants, supporting tasks such as writing, design, programming, and decision-making (Fui-Hoon Nah *et al*., 2023).

Collaborative systems emphasize usability, transparency, and trust, enabling users to interact with AI in intuitive and meaningful ways. For example, generative models can assist in brainstorming ideas, automating repetitive tasks, or providing decision support in complex scenarios. This human-centered approach recognizes that the most effective AI systems are those that complement human expertise rather than operate in isolation (Odunuga *et al*.,2024).

Despite its potential, human-AI collaboration also raises important questions about user dependence, skill degradation, and accountability. Designing systems that empower users while maintaining oversight and control is therefore a key direction for future research (Kunz *et al*., 2025).

5 APPLICATIONS OF GENERATIVE AI

Generative AI has quickly moved away as a research-oriented technology to a workable technology with transformative potentials in a diverse array of fields. Its capability to create, model and reason complex data has placed it not only as a productivity tool, but also a scientific and engineering enabler. Guideline Generative models are becoming more and more integrated in real-world systems, whether in automation or human decision-making, whether in healthcare or robotics. This section identifies the main areas of application where generative AI is already impactful.

5.1 Healthcare and biomedical research

Generative AI is becoming an important aspect of healthcare in improving diagnosis, treatment planning, and drug discovery. Medical images can be analyzed using models, which can produce a diagnostic report and help clinicians identify patterns that might be hidden. Generative models are currently being applied in biomedical studies to create new molecules, predict protein structures, and model biological phenomena (Miracle *et al*., 2025).

Drug discovery has become one of the most promising areas of application, with generative models potentially saving a lot of time and reducing costs associated with the discovery of potential compounds (Gangwal *et al*., 2024). Moreover, synthetic data generation allows the generation of privacy-sensitive datasets to train medical models, overcoming the problem of patient confidentiality. Nonetheless, clinical reliability, regulatory compliance, and ethical use are crucial to ensure widespread adoption (Mendes *et al*., 2025)

5.2 Education and personalized learning

Generative AI is reshaping education by making the learning process highly personalized and adaptive. Generative powered intelligent tutoring systems can be used to personalize content according to the needs, preferences, and performance of individual learners. In real time, these systems can produce explanations, quizzes, and feedback and make learning more interactive and accessible (Mohamed *et al*., 2025).

Moreover, generative AI assists teachers with automating the creation of content, grading, and curriculum design. It also enables the translation of languages and access which assists in closing the gap between education in various regions. In spite of these advantages, issues like ensuring academic integrity, avoiding over-dependence on AI, and equitable access have to be resolved with care (George *et al*., 2023).

5.3 Software engineering and code generation

Generative AI has become an influential software engineering tool in the context of improving developer productivity. The current models are capable of producing code snippets, indicate optimization, debug code, and even help to design complex software architectures. This has greatly minimized the development time, as well as the barrier to entry of programming (Coutinho *et al*., 2024).

In addition to code generation, automated testing, documentation generation, and system maintenance are also being automated using AI systems. Organizations can enhance efficiency and minimize the number of humans involved in development by incorporating generative models into development workflow. Nevertheless, questions about the correctness of the code, security risks, and intellectual property must be properly addressed (Khade *et al*., 2025).

5.4 Creative industries

Creative industries, such as art, music, film, design, and others, are being transformed by generative AI. Artists and creators are employing AI tools in order to create new content, experiment with new styles, and improve their creative experiences (Alabi *et al*., 2024). As an illustration, text-to-image and text-to-video models can be used to create visual content quickly, and music generation models can be used to create original content.

Human creativity and machine intelligence have worked in collaboration and resulted in new forms of expression and innovation. Simultaneously, it brings up critical issues concerning authorship, originality, and copyright. The issue of balancing creativity with ethical and legal remains a persistent challenge in this field (Jadhav *et al*., 2024).

5.5 Business and decision support

Generative AI is finding application in business settings in decision support, customer interaction, and automation of processes. AI is used by organizations to create reports, market trends, and strategic information. Generative model-based chatbots and virtual assistants improve the services provided to customers by providing personalized and context-sensitive services (Nalini *et al*., 2024).

Also, AI can be used in content marketing, financial analysis, and supply chain optimization (Mohamed *et al*., 2023). It facilitates organizations to make better decisions by automating routine operations and giving them data-driven recommendations. Nevertheless, it is important to ensure transparency, reliability, and accountability in AI-driven decision-making (Salih *et al*., 2025).

5.6 Cybersecurity

Generative AI performs two functions in cybercrime, as both an offensive and defensive mechanism. Defensively, AI models are able to identify anomalies, come up with threat intelligence, and simulate cyberattacks to test the vulnerability of the system. Such capabilities increase the capacity of organizations to detect and respond to security threats on-the-fly (Dhoni *et al*, 2023).

On the other hand, bad actors can use generative models to generate advanced phishing, deepfakes, and automated malware. This dynamic threat environment necessitates unceasing improvements in AI-supported security solutions, and sound regulatory and ethics to curb misuse (Jimmy *et al*., 2021).

5.7 Scientific discovery

Generative AI is even being seen as a driver of scientific discovery. AI can speed up the research process in physics, chemistry, and environmental science by simulating complex systems and generating hypotheses. Indicatively, generative models can be used to simulate experiments, make predictions, and detect patterns in large datasets that would otherwise be challenging to analyze by humans (Reddy *et al*., 2025).

This functionality allows the researcher to investigate new concepts in a more effective manner and discover information that might not be obvious at first. Consequently, generative AI is emerging as a powerful tool in interdisciplinary research, closing the data analysis-knowledge creation gap (Lozada *et al*., 2023).

5.8 Robotics and autonomous systems

Generative AI is used in robotics and autonomous systems to enhance perception, planning and interaction. Generative models are robots that are able to reason about complex environments, design action plans and respond to changing conditions. This is especially relevant to the fields of autonomous vehicles, industrial automation, and human-robot collaboration (Thaker *et al*., 2024).

Additionally, generative AI allows simulation-based learning, in which robots can train on simulated environments prior to application in the real world. This minimizes risks and increases robustness of systems. As generative models are still being developed, they will be central to the future development of intelligent, collaborative automation systems through their collaboration with robotics (Yao *et al*., 2025).

In general, generative AI is not limited to specific applications anymore; it is turning into a general-purpose technology that leads to innovation across fields (Dave *et al*., 2025). Its increasingly prominent status as a scientific and engineering enabler underscores its transformative potential and the necessity to develop and deploy it responsibly (Musiol *et al*., 2024).

Even with the impressive advancement of the generative AI, there are a number of key issues that still restrict its reliability, trustworthiness, and wide usage. Among the most notable ones, there is the so-called phenomenon of hallucination when models produce outputs that seem logical and well-constructed but are not factual or downright untrue (Adel *et al*., 2025). This issue is especially alarming in such high stakes areas as in healthcare, law, and finance, where misinformation can have severe repercussions. The root cause of hallucination is that generative models are probabilistic and focus more on fluency compared to factuality when used outside the training distribution or when they have no access to verified external knowledge sources (Ajuzieogu *et al*., 2024).

Intimately tied with reliability issues are the concerns of bias and fairness. Generative models are trained on large-scale data that tends to be biased historically, culturally and socially. These models can thereby unintentionally reproduce, or even enhance, discriminatory trends in the data (Afreen *et al*., 2025). Discrimination may be realized in different forms such as gender, racial, and social-economic differences in the products created. It is not always easy to deal with these biases, both in technical terms (debiasing algorithms and curated datasets) and in terms of ethical and social consequences. The issue of ensuring fairness in generative AI systems is a complex and current research problem (Lopez *et al*., 2021).

Another challenge is privacy and data security. Standard training large generative models often requires large quantities of data, some of which might include sensitive or personally identifiable information (Golda *et al*., 2024). There is an element of risk that such information can be inadvertently memorized and reproduced by models, and result in possible privacy violation. Moreover, the introduction of generative AI into the systems that process sensitive information also brings up the issue of information leakage, unauthorized access, and regulatory compliance (Uddagiri *et al*., 2024). Differential privacy, federated learning, and secure model training are among the techniques being investigated to reduce these risks, but it is hard to apply them in practice at scale (Zhang *et al*. 2022).

The implementation of generative AI is also complicated by legal and regulatory concerns, especially copyright and intellectual property. Because such models are trained using large amounts of publicly available and proprietary data, there is a question of ownership of the raw training data and the resulting outputs (Lucchi *et al*., 2024). To illustrate, sometimes it is not clear when AI-generated content violates the current copyrights and who is entitled to such content. Intellectual property is a key aspect of industries that face challenges due to these uncertainties like media, publishing, and software development. With the legal frameworks unable to keep up with the technological progress, more explicit guidelines and policies are in high demand (Zakir *et al*., 2024).

Lack of explainability and transparency of generative models is another significant drawback. Numerous sophisticated AI systems, especially large neural networks, are run as black boxes, which is why it is hard to comprehend how certain results are produced (Hassija *et al*., 2024). This is not interpretable, which makes it difficult to trust, particularly in processes where accountability and justification of decisions are critical (Barnes *et al*., 2024). Scientists are working on ways to enhance explainability, such as visualizing attention, techniques of model interpretability, and hybrid methods that combine neural networks with symbolic reasoning. Nevertheless, the balancing between the complexity of the model and its interpretability is still a major challenge (Mi *et al*., 2020).

The environmental and computational cost-effort of training and deploying large-scale generative models is also turning out to be an increasing concern. State-of-the-art models take a lot of computation, which may bring in large data centers consuming a lot of energy to train them (Chakraborty *et al*., 2024). This not only adds the cost of development financially but also adds to carbon emission and environmental impact.

With the further growth of AI, energy-efficient architectures, optimization strategies, and hardware are highly needed to guarantee sustainable development (Mitu *et al*., 2024).

Lastly, there is a risk of generative AI being misapplied and it is dangerous to society. Deepfakes and other technologies that generate content automatically can be used to spread false information, sway the population, and commit fraud (Sophia *et al*., 2025). The possibility of creating extremely realistic text, pictures, sounds, and videos has turned it into an even tougher task to draw the line between genuine and fake information (Ghiurău *et al*., 2024). This drastically affects media integrity, politics, and trust of the people. To deal with these risks, both technical protections, including detection systems and watermarking, and regulatory and ethical interventions are in order (Liu *et al*., 2025).

In general, the existing literature is unanimous that misinformation, bias, privacy issues, cybersecurity threats, intellectual property issues, and environmental requirements are key impediments to the responsible use of generative AI. To overcome such limitations, the concerted actions at technical, regulatory, and social levels will be needed to make generative AI systems effective and trustworthy (Al-Kfairy *et al*., 2024).

6 ETHICAL, LEGAL, AND SOCIAL IMPLICATIONS

6.1 Responsible AI governance

The fast development of generative AI has presented not only technical but also various ethical, legal, and social consequences that need to be properly addressed in order to make the application of generative AI responsible and sustainable (Mitra *et al*., 2025). With the growing integration of these systems into vital areas of society, issues that emerge about governance, accountability, and societal influence have become the center of research and policy debate (Head *et al*., 2022).

6.2 Human oversight

Intimately connected to governance is the significance of human control. Although generative AI systems can be used to accomplish complex tasks, with or without human intervention, human intervention is essential, especially in applications with high stakes (Holzinger *et al*., 2025). Human control will make sure that the decisions that are made or backed by the AI systems can be reviewed, validated and corrected when need be. This is particularly crucial in areas like health care, legal procedures, and government policy where mistakes or unforeseen consequences may have critical consequences (Ottun *et al*., 2025). One of the challenges, therefore, is to design systems that can be successfully used to combine human judgment and automated capabilities.

6.3 Accountability

The problem of accountability also makes the implementation of generative AI more difficult. In cases where AI systems generate harmful or wrong results, it is not always clear whether the developers of the model, the organization that deployed them, or the end users should be held responsible (Kumar *et al*.,2025). This ambiguity presents both legal and ethical issues, especially when it comes to the instances of financial loss, misinformation, or harm to individuals. It is imperative to develop transparent accountability models to ensure that each role is clearly defined and that there are redress and liability mechanisms (Hossain *et al*., 2024).

6.4 AI safety

AI safety is another important dimension that aims to ensure that AI systems act as desired and will not produce unintended harm. Safety issues in the generative models context involve managing harmful outputs, preventing malicious use, and ensuring that model behavior aligns with human values (Lin *et al*., 2025). To enhance safety, alignment training, content filtering, and reinforcement learning based on human feedback have been suggested. Nevertheless, the development of strong and scalable safety is still a research problem, especially when models become more sophisticated and autonomous (Gu *et al*.,2024).

6.5 Regulatory frameworks

The process of creating regulatory frameworks is also gaining more and more popularity in the world. Governments and international bodies are in the process of putting in place policies to mitigate the risks and opportunities brought about by AI (Abbott *et al*.,2021). These structures are also intended to make sure that legal provisions regarding data protection, intellectual property and ethical usage are met, as well as innovation. Nevertheless, the speed at which technology is evolving tends to surpass regulatory development and create loopholes and differences between regions. The need to harmonize regulations on a global scale is still a major challenge (Kumar *et al*., 2024).

6.6 Social impact on labor and creativity

Last but not least, the generative AI social effect on labor and creativity is quite a controversial subject. On the one hand, AI can increase the level of productivity, automatize repetitive processes, and open up additional prospects in all industries (Wach *et al*., 2023). Conversely, it can cause the disruption of traditional job positions, which contributes to the displacement of the workforce and necessitates reskilling. Creative markets Generative AI is also changing the nature of authorship and creative expression in creative industries, making originality, ownership and human creativity controversial. Some consider AI as an instrument that enhances human abilities, others worry that AI will reduce human agency and importance (Oyetade *et al*., 2025).

Ethical, legal and social implications of generative AI are complex and intertwined. To tackle these issues, a multi-sector effort with researchers, industry leaders, policymakers and the society is necessary. It is important to ensure that generative AI systems are created and implemented in a responsible, transparent, and human-centered way to maximize their advantages and reduce any possible harm.

7 FUTURE RESEARCH DIRECTIONS

As generative AI systems advance, future research needs to shift focus from increasing capabilities to building systems that are safe, efficient, and user-centred.

Existing models show remarkable capabilities, but with some challenges that point to more reliable, efficient, and human-friendly development. This section highlights some of the primary areas of research that will advance future generative AI systems..

7.1 Trustworthy and explainable generative AI

One of the major future research directions is the development of trustful and explainable generative AI. As further applications are deployed in critical applications, users must have confidence in and read the results. This includes improving the transparency of models, reducing hallucinations and providing meaningful explanations to AI-generated results. Some of the promising techniques are explaining AI (XAI), attention maps, and symbolic-neural hybrid models, yet there is still a challenge of balancing interpretability and model performance.

7.2 Energy-efficient AI

The growing scale of generative models has been a major energy and environmental concern. The area of energy-efficient AI is an urgent priority in future work, and the reduction of energy requirements of training and inference is prioritized (Alzu'bi *et al*., 2025). Energy consumption can be reduced by techniques such as model compression, sparsity, efficient training algorithms, and hardware design. Sustainable AI systems are essential because they benefit the environment, but also democratize access to advanced AI to more users and businesses (Deng *et al*., 2020).

7.3 Domain-specific foundation models

Despite the impressive flexibility of foundation models, increasing interest has been given to the development of domain-specific models in particular applications. By using domain knowledge and data, such models can be more accurate and resilient (ZHAO *et al*, 2023). As an example, health, finance and legal application models should be aware of domain language and constraints. Future studies are required on how to effectively develop, upgrade and maintain these models without breaking domain specific rules and regulations (Chen *et al*., 2024).

7.4 Continual and lifelong learning

Existing generative models are typically trained only once, which does not allow them to constantly acquire new information. Continuous and lifelong learning attempts to counter this as models are able to learn and adjust to new information whilst retaining old information. This is particularly important in dynamic environments where data is changing rapidly (Salakhutdinov *et al*, 2015). To create resilient and robust systems, it will be necessary to address problems such as catastrophic forgetting, data drift, and the efficiency of model update.

7.5 Multimodal reasoning

In the future, it is anticipated that generative AI systems will transcend unimodal processing and evolve to multimodal reasoning. It refers to the principled, context-sensitive reasoning about more than one type of data (text, image, audio, video). Smart assistants, robots and immersive virtual worlds will be facilitated by multimodal architectures. However, the problem of modality-based representations and reasoning integration remains a research question (Kaur *et al*., 2025).

7.6 Human-centered AI design

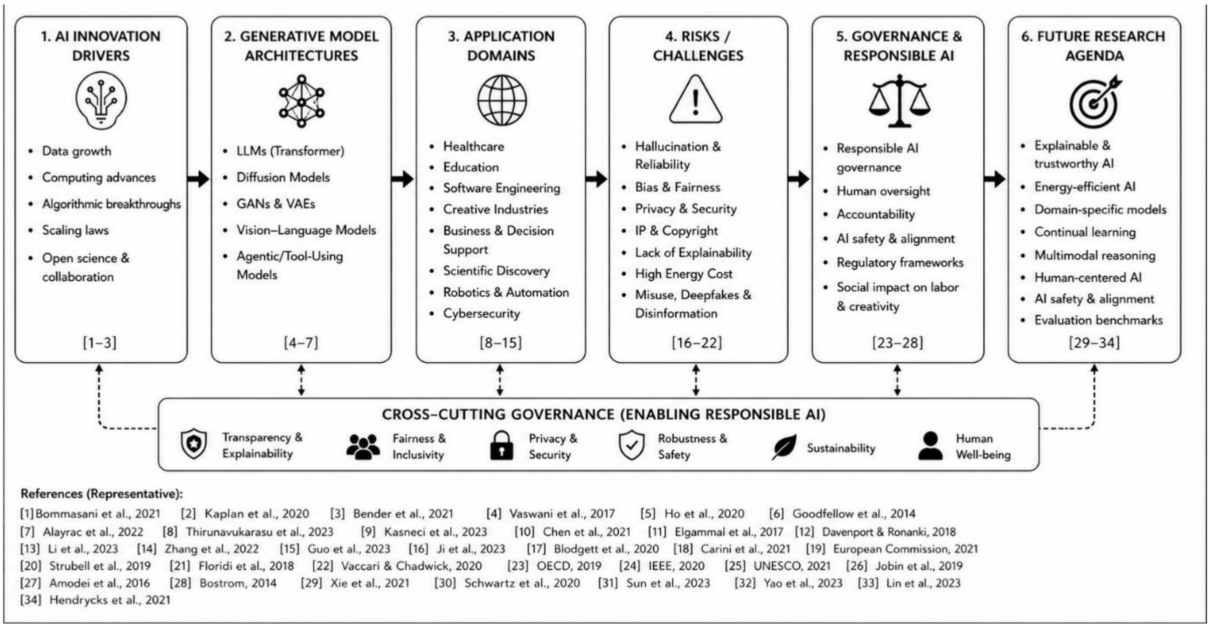
Human-centered AI design is one of the key points to concentrate on in the future. The research must be more usable, more accessible and more about the trust of the user other than the technical performance (Margetis *et al*., 2021). This includes designing user-friendly interfaces, giving users the ability to determine the AI system, and making the system reflect human values and priorities. Inclusion is also an aspect of user-centred design, where AI systems are designed in ways that are beneficial to many users (Schmager *et al*., 2025).

7.7 AI safety and alignment

It is imperative that AI systems that are generated to act must act as humans would want them to in accordance with human values (Gabriel *et al*., 2020). The AI safety and alignment field considers methods to make sure that model behaviour aligns with human values and expectations (Singh *et al*., 2025).

Figure 1

Proposed Conceptual Framework for Advanced AI and Generative Models



The proposed conceptual framework offers a systematic flow depicting how innovations in artificial intelligence become viable and accountable generative AI systems. It starts by examining the main drivers of AI innovation, including data availability, computational power, and algorithmic advances, that make it possible to create different architectures of generative models, including large language models, diffusion models, and multimodal systems. These architectures are further implemented in a wide range of fields including healthcare, education, software engineering, and robotics, which evidences their far-reaching influence. Nevertheless, their implementation presents serious risks and challenges, such as reliability concerns, bias, privacy, and high computation costs. The framework, in response to these issues, focuses on governance and responsible AI practices, such as human supervision, accountability, safety controls, and compliance regulation. Lastly, it points to future research directions that aim to enhance trust, efficiency, domain specialization, and real-world evaluation. On the whole, the framework highlights the fact that innovation, application, risk management, and governance are interconnected processes that influence the development of sustainable and reliable generative AI systems.

8 DISCUSSION

The development of generative AI is evolving fast, which is a delicate combination of mind-blowing opportunities and threats. On the one hand, generative models have already opened up a range of unparalleled opportunities in the area of automatization, creativity, and knowledge generation (Mhlanga *et al*.,2024). They are able to improve the efficiency of several areas like healthcare, education, and software engineering and make decisions faster, provide services tailored to the needs of customers, and solve problems (Kumar *et al*., 2025).

For instance, in the field of drug discovery and science, generative AI can expedite the innovation process by scanning vast solution spaces that are not accessible through manual search. On the other hand, the benefits come with big hazards, like outputs that aren't real, hidden biases, privacy concerns, and the possibility of being misused, like in deepfakes and false information. The bi-directional nature of generative AI underscores the necessity for a balanced approach to innovation and protection to ensure ethical usage (Grinbaum *et al*., 2024).People frequently think of generative AI as a game-changing technology since it changes the sort of system from one that is only good for certain tasks to one that can learn and adapt. In contrast to previous AI models that were limited to specific tasks, generative systems are capable of performing a wide variety of functions across various disciplines with minimal changes (Pescapè *et al*., 2024). They are the most important instruments for scientific and industrial discovery because they can create content, model complex situations, and help with reasoning tasks. Furthermore, the combination of multimodal functionality and agent-based systems suggests a shift toward more autonomous and interactive AI, which will radically transform how humans interact with technology. A transformation in society as well as technology changes how people work, make decisions, and create (Kotsis *et al*., 2025).

Although these advances have been made, there are still a number of significant research gaps. Among the most important loopholes is the absence of effective mechanisms to promote factual accuracy and reliability especially in real-world implementation where inaccuracies can be detrimental to practice (Roy *et al*.,2024). The next important gap is explainability since existing models tend to be black box, which limits the trust and responsibility of the users (Thalpage *et al*., 2023). Moreover, more viable ways of reducing bias and promoting fairness among different populations are required. Technically, there is still no solution to the issue of making large-scale models efficient and ensuring they have a lower environmental footprint. There is an increasing demand also of standardized evaluation frameworks beyond benchmark performance and to evaluate real world reliability, safety, and compliance with ethical standards. These gaps will be critical in the transition of generative AI as an experimental system into reliable, widely used technologies.

9 CONCLUSION

Generative artificial intelligence (AI) represents a paradigm shift in computing, enabling systems to generate, think, and communicate in a broad spectrum of applications. In this paper discusses the history of the generative models and their architectural principles and their increasing use in the practical applications. Although the advantages of using these technologies are the enormous in terms of the enhanced efficiency accelerated innovation and improved decision making. They poses significant problems concerning trust, privacy, fairness and ethical integrity. To solve these problems, an interdisciplinary solution is required which incorporates technological innovations, governance structures, regulatory measures and human based design principles. The framework introduced in thi article explains how complicated innovation, application, responsibility and risk are there and how a balanced and holistic approach to AI development should be there. In future research should be more attention to development of effective, precise and comprehensible systems that are more consistent with human values. It will also necessary to set the strict and realistic evaluation criteria to make them practical in the real world. In the last, the sustained usefulness of creative AI will not only rely on its technical potential but also on the capacity to ensure safety, transparency, and equity in various social situations.

REFERENCES

Abbott, K. W., & Snidal, D. (2021). The governance triangle: Regulatory standards institutions and the shadow of the state. In *The spectrum of international institutions* (pp. 52-91). Routledge.

Abukmeil, M., Ferrari, S., Genovese, A., Piuri, V., & Scotti, F. (2021). A survey of unsupervised generative models for exploratory data analysis and representation learning. *Acm computing surveys (csur)*, *54*(5), 1-40.

Adel, A., & Alani, N. (2025). Can generative AI reliably synthesise literature? exploring hallucination issues in ChatGPT. *AI & SOCIETY*, 1-14.

Afreen, J., Mohaghegh, M., & Doborjeh, M. (2025). Systematic literature review on bias mitigation in generative AI. *AI and Ethics*, *5*(5), 4789-4841.

Afreen, J., Mohaghegh, M., & Doborjeh, M. (2025). Systematic literature review on bias mitigation in generative AI. *AI and Ethics*, *5*(5), 4789-4841.

Afreen, J., Mohaghegh, M., & Doborjeh, M. (2025). Systematic literature review on bias mitigation in generative AI. *AI and Ethics*, *5*(5), 4789-4841.

Ahmed, S. F., Alam, M. S. B., Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., ... & Gandomi, A. H. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. *Artificial Intelligence Review*, *56*(11), 13521-13617.

Ajuzieogu, U. C. (2024). Towards Hallucination-Resilient AI: Navigating Challenges Ethical Dilemmas and Mitigation Strategies. *AI Ethics Journal*.

Akkem, Y., Biswas, S. K., & Varanasi, A. (2024). A comprehensive review of synthetic data generation in smart farming by using variational autoencoder and generative adversarial network. *Engineering Applications of Artificial Intelligence*, *131*, 107881.

Alabi, M. (2024). Generative AI and its Applications in Creative Industries.

Al-Kfairy, M., Mustafa, D., Kshetri, N., Insiew, M., & Alfandi, O. (2024, August). Ethical challenges and solutions of generative AI: An interdisciplinary perspective. In *Informatics* (Vol. 11, No. 3, p. 58). MDPI.

Alzu'bi, S., Kanan, T., Elbes, M., Kanaan, G., & Trrad, I. (2025). Energy-efficient edge deployment of generative AI models using federated learning. *Cluster computing*, *28*(5), 315.

Awais, M., Naseer, M., Khan, S., Anwer, R. M., Cholakkal, H., Shah, M., ... & Khan, F. S. (2025). Foundation models defining a new era in vision: a survey and outlook. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *47*(4), 2245-2264.

Balkrishna Rasiklal, Y. (2024). Exploring Multimodal Generative AI: A Comprehensive Review of Image, Text, and Audio Integration. *Innovative: International Multi-disciplinary Journal of Applied Technology*, *2*(10), 124-133.

Barnes, E., & Hutson, J. (2024). Navigating the complexities of AI: The critical role of interpretability and explainability in ensuring transparency and trust. *International Journal of Multidisciplinary and Current Educational Research*, *6*(3).

Basiouni, A. M., El Rashid, M., & Shaalan, K. (2025). In-context learning in large language models (LLMs): Mechanisms, capabilities, and implications for advanced knowledge representation and reasoning. *IEEE Access*.

Bengesi, S., El-Sayed, H., Sarker, M. K., Houkpati, Y., Irungu, J., & Oladunni, T. (2024). Advancements in generative AI: A comprehensive review of GANs, GPT, autoencoders, diffusion model, and transformers. *IEEe Access*, *12*, 69812-69837.

Berti, L., Giorgi, F., & Kasneci, G. (2025). Emergent abilities in large language models: A survey. *arXiv preprint arXiv:2503.05788*.

Bhatt, D., Patel, C., Talsania, H., Patel, J., Vaghela, R., Pandya, S., ... & Ghayvat, H. (2021). CNN variants for computer vision: History, architecture, application, challenges and future scope. *Electronics*, *10*(20), 2470.

Bordes, F., Pang, R. Y., Ajay, A., Li, A. C., Bardes, A., Petryk, S., ... & Chandra, V. (2024). An introduction to vision-language modeling. *arXiv preprint arXiv:2405.17247*.

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, *35*(5), 1589-1607.

Chaitanya, K., & Rolla, K. J. (2024). The Evolution and Impact of Large Language Models in Artificial Intelligence. In *Algorithms in Advanced Artificial Intelligence* (pp. 410-417). CRC Press.

Chakraborty, T., Reddy KS, U., Naik, S. M., Panja, M., & Manvitha, B. (2024). Ten years of generative adversarial nets (GANs): a survey of the state-of-the-art. *Machine Learning: Science and Technology*, *5*(1), 011001.

Chakraborty, T., Reddy KS, U., Naik, S. M., Panja, M., & Manvitha, B. (2024). Ten years of generative adversarial nets (GANs): a survey of the state-of-the-art. *Machine Learning: Science and Technology*, *5*(1), 011001.

Chen, Z. Z., Ma, J., Zhang, X., Hao, N., Yan, A., Nourbakhsh, A., ... & Wang, W. Y. (2024). A survey on large language models for critical societal domains: Finance, healthcare, and law. *arXiv preprint arXiv:2405.01769*.

Chen, Z., Xu, L., Zheng, H., Chen, L., Tolba, A., Zhao, L., ... & Feng, H. (2024). Evolution and Prospects of Foundation Models: From Large Language Models to Large Multimodal Models. *Computers, Materials & Continua*, *80*(2).

Coutinho, M., Marques, L., Santos, A., Dahia, M., França, C., & de Souza Santos, R. (2024, July). The role of generative ai in software development productivity: A pilot case study. In *Proceedings of the 1st ACM International Conference on AI-Powered Software* (pp. 131-138).

Croitoru, F. A., Hondru, V., Ionescu, R. T., & Shah, M. (2023). Diffusion models in vision: A survey. *IEEE transactions on pattern analysis and machine intelligence*, *45*(9), 10850-10869.

Dave, E., Adeola, F., & Noel, D. (2025). Generative AI and Foundation Models: Redefining Intelligence, Creativity, and Scalability in the Digital Era.

Deng, L., Li, G., Han, S., Shi, L., & Xie, Y. (2020). Model compression and hardware acceleration for neural networks: A comprehensive survey. *Proceedings of the IEEE*, *108*(4), 485-532.

Dhoni, P., & Kumar, R. (2023). Synergizing generative ai and cybersecurity: Roles of generative ai entities, companies, agencies, and government in enhancing cybersecurity. *Authorea Preprints*.

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of information technology case and application research*, *25*(3), 277-304.

Gabriel, I. (2020). Artificial Intelligence, Values, and Alignment: I. Gabriel. *Minds and machines*, *30*(3), 411-437.

Gangwal, A., Ansari, A., Ahmad, I., Azad, A. K., Kumarasamy, V., Subramaniyan, V., & Wong, L. S. (2024). Generative artificial intelligence in drug discovery: basic framework, recent advances, challenges, and opportunities. *Frontiers in pharmacology*, *15*, 1331062.

George, A. S. (2023). The potential of generative AI to reform graduate education. *Partners Universal International Research Journal*, *2*(4), 36-50.

Ghiurău, D., & Popescu, D. E. (2024). Distinguishing reality from AI: approaches for detecting synthetic content. *Computers*, *14*(1), 1.

Ghosh, A., Acharya, A., Saha, S., Jain, V., & Chadha, A. (2024). Exploring the frontier of vision-language models: A survey of current methodologies and future directions. *arXiv preprint arXiv:2404.07214*.

Girin, L., Leglaive, S., Bie, X., Diard, J., Hueber, T., & Alameda-Pineda, X. (2022). Dynamical variational autoencoders: A comprehensive review. *Foundations and Trends in Machine Learning*, *15*(1-2), 1-175.

Golda, A., Mekonen, K., Pandey, A., Singh, A., Hassija, V., Chamola, V., & Sikdar, B. (2024). Privacy and security concerns in generative AI: A comprehensive survey. *Ieee Access*, *12*, 48126-48144.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, *63*(11), 139-144.

Grimm, V., Augusiak, J., Focks, A., Frank, B. M., Gabsi, F., Johnston, A. S., ... & Railsback, S. F. (2014). Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. *Ecological modelling*, *280*, 129-139.

Grinbaum, A., & Adomaitis, L. (2024). Dual use concerns of generative AI and large language models. *Journal of Responsible Innovation*, *11*(1), 2304381.

Gu, S., Yang, L., Du, Y., Chen, G., Walter, F., Wang, J., & Knoll, A. (2024). A review of safe reinforcement learning: Methods, theories, and applications. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *46*(12), 11216-11235.

Gupta, S., Ranjan, R., & Singh, S. N. (2024). A comprehensive survey of retrieval-augmented generation (rag): Evolution, current landscape and future directions. *arXiv preprint arXiv:2410.12837*.

Han, B., Susnjak, T., & Mathrani, A. (2024). Automating systematic literature reviews with retrieval-augmented generation: A comprehensive overview. *Applied Sciences*, *14*(19), 9103.

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., ... & Hussain, A. (2024). Interpreting black-box models: a review on explainable artificial intelligence. *Cognitive Computation*, *16*(1), 45-74.

Head, B. W. (2022). *Wicked problems in public policy: Understanding and responding to complex challenges* (p. 176). Springer Nature.

Holzinger, A., Zatloukal, K., & Müller, H. (2025). Is human oversight to AI systems still possible?. *New Biotechnology*, *85*, 59-62.

Hossain, M. Z., Kibria, H., & Johora, F. T. (2024). Ethical challenges in forensic accounting: Balancing professional responsibility and legal obligations. *Open Journal of Accounting*, *13*(3), 57-73.

Huang, Y., Xu, J., Lai, J., Jiang, Z., Chen, T., Li, Z., ... & Zhao, P. (2023). Advancing transformer architecture in long-context large language models: A comprehensive survey. *arXiv preprint arXiv:2311.12351*.

Jadhav, S., Patil, J. A., Jyoti, R. R., Kanase, O. S., & Khadde, M. S. (2024, August). The future of content creation: leveraging AI for code, text, music, and video generation. In *2024 8th International Conference on Computing, Communication, Control and Automation (ICCUBEA)* (pp. 1-7). IEEE.

Jimmy, F. (2021). Emerging threats: The latest cybersecurity risks and the role of artificial intelligence in enhancing cybersecurity defenses. *Valley International Journal Digital Library*, *1*(2), 564-574.

Jin, Y., Wang, Y., Long, M., Wang, J., Philip, S. Y., & Sun, J. (2020, July). A Multi-Player Minimax Game for Generative Adversarial Networks. In *ICME* (pp. 1-6).

Johnsen, M. (2024). *AI Alignment*. Maria Johnsen.

Karanikolas, N., Manga, E., Samaridi, N., Tousidou, E., & Vassilakopoulos, M. (2023, November). Large language models versus natural language understanding and generation. In *Proceedings of the 27th Pan-Hellenic Conference on Progress in Computing and Informatics* (pp. 278-290).

Katharopoulos, A., Vyas, A., Pappas, N., & Fleuret, F. (2020, November). Transformers are rnns: Fast autoregressive transformers with linear attention. In *International conference on machine learning* (pp. 5156-5165). PMLR.

Kaur, H., Kishor Kumar Reddy, C., Manoj Kumar Reddy, D., & Hanafiah, M. M. (2025). Single Modality to Multi-modality: The Evolutionary Trajectory of Artificial Intelligence in Integrating Diverse Data Streams for Enhanced Cognitive Capabilities. In *Multimodal Generative AI* (pp. 297-322). Singapore: Springer Nature Singapore.

Khade, P. S., & Sambhe, D. R. U. (2025). Artificial Intelligence in Software Development: A Review of Code Generation, Testing, Maintenance and Security. *International Journal of Current Science Research and Review*, *8*(4), 1632-1641.

Khan, S., Naseer, M., Hayat, M., Zamir, S. W., Khan, F. S., & Shah, M. (2022). Transformers in vision: A survey. *ACM computing surveys (CSUR)*, *54*(10s), 1-41.

Korteling, J. E., van de Boer-Visschedijk, G. C., Blankendaal, R. A., Boonekamp, R. C., & Eikelboom, A. R. (2021). Human-versus artificial intelligence. *Frontiers in artificial intelligence*, *4*, 622364.

Kotsis, K. T. (2025). Artificial intelligence and the scientific process: A review of ChatGPT's role to foster experimental thinking in physics education. *European Journal of Contemporary Education and E-Learning*, *3*(3), 183-198.

Kumar, K., & Poonam. (2025). Responsible AI: Ethical Considerations in Generative AI. *Textual Intelligence: Large Language Models and Their Real-World Applications*, 413-434.

Kumar, P. (2024). Intellectual property rights (IPR): nurturing creativity, fostering innovation. *ldealistic Journal of Advanced Research in Progressive Spectrums (IJARPS) eISSN–2583-6986*, *3*(02), 32-38.

Kumar, S., Machireddy, J. R., Sankaran, T., & Sholapurapu, P. K. (2025). Integration of machine learning and data science for optimized decision-making in computer applications and engineering. *Journal of Information Systems Engineering and Management*, *10*.

Kunz, W. H., Sajtos, L., & Flavián, C. (2025). Beyond replacement: human-machine collaboration in the age of AI. *Journal of Service Management*, *36*(4), 477-494.

Li, Z., Li, H., & Meng, L. (2023). Model compression for deep neural networks: A survey. *Computers*, *12*(3), 60.

Liang, C., Du, H., Sun, Y., Niyato, D., Kang, J., Zhao, D., & Imran, M. A. (2024). Generative AI-driven semantic communication networks: Architecture, technologies, and applications. *IEEE Transactions on Cognitive Communications and Networking*, *11*(1), 27-47.

Lin, Z., Sun, H., & Shroff, N. (2025). Ai safety vs. ai security: Demystifying the distinction and boundaries. *arXiv preprint arXiv:2506.18932*.

Liu, F., & Panagiotakos, D. (2022). Real-world data: a brief review of the methods, applications, challenges and opportunities. *BMC Medical Research Methodology*, *22*(1), 287.

Liu, M. Y., Huang, X., Yu, J., Wang, T. C., & Mallya, A. (2021). Generative adversarial networks for image and video synthesis: Algorithms and applications. *Proceedings of the IEEE*, *109*(5), 839-862.

Liu, X., Xu, R., & Chen, Y. (2025). Securing Digital Media Integrity: A Survey of Watermarking and Manipulation Detection for Image Authentication. *Authorea Preprints*.

Lopez, P. (2021). Bias does not equal bias: A socio-technical typology of bias in data-based algorithmic systems. *Internet Policy Review*, *10*(4), 1-29.

Lozada, N., Arias-Pérez, J., & Henao-García, E. A. (2023). Unveiling the effects of big data analytics capability on innovation capability through absorptive capacity: why more and better insights matter. *Journal of Enterprise Information Management*, *36*(2), 680-701.

Lu, Y., Chen, L., Zhang, Y., Shen, M., Wang, H., Wang, X., ... & Wei, W. (2023). Machine learning for synthetic data generation: a review. *arXiv preprint arXiv:2302.04062*.

Lucchi, N. (2024). ChatGPT: a case study on copyright challenges for generative artificial intelligence systems. *European Journal of Risk Regulation*, *15*(3), 602-624.

Luo, Q., Zeng, W., Chen, M., Peng, G., Yuan, X., & Yin, Q. (2023, July). Self-attention and transformers: Driving the evolution of large language models. In *2023 IEEE 6th International conference on electronic information and communication technology (ICEICT)* (pp. 401-405). IEEE.

Mai, X., Tao, Z., Lin, J., Wang, H., Chang, Y., Kang, Y., ... & Zhang, W. (2024). From efficient multimodal models to world models: A survey. *arXiv preprint arXiv:2407.00118*.

Margetis, G., Ntoa, S., Antona, M., & Stephanidis, C. (2021). Human-centered design of artificial intelligence. *Handbook of human factors and ergonomics*, 1085-1106.

Mendes, J. M., Barbar, A., & Refaie, M. (2025). Synthetic data generation: a privacy-preserving approach to accelerate rare disease research. *Frontiers in Digital Health*, *7*, 1563991.

Mhlanga, D. (2024). Generative AI for emerging researchers: the promises, ethics, and risks. *Ethics, and Risks*, 1-25.

Mi, J. X., Li, A. D., & Zhou, L. F. (2020). Review study of interpretation methods for future interpretable machine learning. *Ieee Access*, *8*, 191969-191985.

Min, B., Ross, H., Sulem, E., Veyseh, A. P. B., Nguyen, T. H., Sainz, O., ... & Roth, D. (2023). Recent advances in natural language processing via large pre-trained language models: A survey. *ACM Computing Surveys*, *56*(2), 1-40.

Miracle, A. A., & Adaobi, C. C. (2025). The impact of generative AI on healthcare. In *Generative Artificial Intelligence (AI) Approaches for Industrial Applications* (pp. 169-188). Cham: Springer Nature Switzerland.

Mishra, R. K., Mishra, D., & Agarwal, R. (2025). Artificial intelligence and intelligent systems. *ARTIFICIAL INTELLIGENCE*.

Mitra, S., Behera, I., Arun, A., & Patnaik, S. (2025). Generative Artificial Intelligence Vis-À-Vis: Social, Ethical and Legal Issues. In *Social, Ethical and Legal Aspects of Generative AI: Tools, Techniques and Systems* (pp. 121-146). Cham: Springer Nature Switzerland.

Mitu, N. E., & Mitu, G. T. (2024). The hidden cost of AI: carbon footprint and mitigation strategies. *Revista de Stiinte Politice*, (84), 9-16.

Mohamed, F. N., Azhar, J., Yasmeen, S., Hussain, I., & Khawar, M. (2025). Generative artificial intelligence and personalized learning environment: Challenges and opportunities. *Southern Journal of Computer Science*, *1*(01), 1-36.

Mohamed, O. A. M. (2023). How generative AI transforming supply chain operations and efficiency?.

Mohebbi Moghaddam, M., Boroomand, B., Jalali, M., Zareian, A., Daeijavad, A., Manshaei, M. H., & Krunz, M. (2023). Games of GANs: game-theoretical models for generative adversarial networks. *Artificial Intelligence Review*, *56*(9), 9771-9807.

Mundlamuri, R., Gunnam, G. R., Mysari, N. K., & Pujuri, J. (2025). The Evolution of AI: From Classical Machine Learning to Modern Large Language Models. *Ieee Access*.

Musiol, M. (2024). *Generative AI: Navigating the course to the artificial general intelligence future*. John Wiley & Sons.

Nalini, R. (2024). Transformative power of artificial Intelligence in decision-making, automation, and customer engagement. In *Complex AI dynamics and interactions in management* (pp. 189-208). IGI Global Scientific Publishing.

Namiot, D., & Ilyushin, E. (2022). Generative Models in Machine Learning. *International Journal of Open Information Technologies*, *10*(7), 101-118.

Odunuga, A., & Franklin, E. T. (2024). Human-AI Collaboration: UX Strategies for Designing Intuitive and Assistive AI Interfaces. *J Artif Intell Mach Learn & Data Sci 2024*, *3*(1), 2495-2503.

Ottun, A. R. O., & Flores, H. (2025). Trustworthy AI in Practice: A Comprehensive Review of Human Oversight and Human-in-the-Loop Approaches. *Authorea Preprints*.

Oyetade, K., & Zuva, T. (2025). A review of generative AI's impact on workforce transformation and future skill requirements. *OIDA International Journal of Sustainable Development*, *18*(12), 187-196.

Pescapè, A. (2024). Exploring the current state and future potential of generative artificial intelligence using a generative artificial intelligence. In *Mind, Body, and Digital Brains* (pp. 37-56). Cham: Springer Nature Switzerland.

Pilot, A. (2025). *Exploring the Role of Artificial Intelligence in Interdisciplinary Model-Based Building Design and Planning in Education: Investigating the Potential for Enhanced Collaboration and Learning Through the Use of AI-Driven Design Tools* (Doctoral dissertation, ETH Zurich).

Qin, Y., Hu, S., Lin, Y., Chen, W., Ding, N., Cui, G., ... & Sun, M. (2024). Tool learning with foundation models. *ACM Computing Surveys*, *57*(4), 1-40.

Rahman, M. I. (2025). *Study of Generative Artificial Intelligence with machine learning and deep learning*. Academic Guru Publishing House.

Raiaan, M. A. K., Mukta, M. S. H., Fatema, K., Fahad, N. M., Sakib, S., Mim, M. M. J., ... & Azam, S. (2024). A review on large language models: Architectures, applications, taxonomies, open issues and challenges. *IEEE access*, *12*, 26839-26874.

Razzaq, K., & Shah, M. (2025). Machine learning and deep learning paradigms: From techniques to practical applications and research frontiers. *Computers*, *14*(3), 93.

Reddy, C. K., & Shojaee, P. (2025, April). Towards scientific discovery with generative ai: Progress, opportunities, and challenges. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 39, No. 27, pp. 28601-28609).

Regenwetter, L., Nobari, A. H., & Ahmed, F. (2022). Deep generative models in engineering design: A review. *Journal of Mechanical Design*, *144*(7), 071704.

Regis, M., Serra, P., & Van Den Heuvel, E. R. (2022). Random autoregressive models: A structured overview. *Econometric Reviews*, *41*(2), 207-230.

Roy, P. (2024). Enhancing real-world robustness in AI: challenges and solutions. *J. Recent Trends Comput. Sci. Eng*, *12*(1), 34-49.

Rusum, G. P., & Anasuri, S. (2023). Synthetic Test Data Generation Using Generative Models. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(4), 96-108.

Ruthotto, L., & Haber, E. (2021). An introduction to deep generative modeling. *GAMM-Mitteilungen*, *44*(2), e202100008.

Salakhutdinov, R. (2015). Learning deep generative models. *Annual Review of Statistics and Its Application*, *2*(1), 361-385.

Salih, S., Husain, O., Abdalla, E. A. M., Ibrahim, A. O., Hashim, A. H. A., Elshafie, H., & Motwakel, A. (2025). Generative AI for industry transformation: a systematic review of chatgpt's capabilities and integration challenges. *International Journal of Computer Science & Network Security*, *25*(5), 221-249.

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN computer science*, *2*(3), 1-21.

Schmager, S., Pappas, I. O., & Vassilakopoulou, P. (2025). Understanding Human-Centred AI: a review of its defining elements and a research agenda. *Behaviour & Information Technology*, *44*(15), 3771-3810.

Schneider, J., Meske, C., & Kuss, P. (2024). Foundation Models: J. Schneider *et al*. *Business & Information Systems Engineering*, *66*(2), 221-231.

Sengar, S. S., Hasan, A. B., Kumar, S., & Carroll, F. (2025). Generative artificial intelligence: a systematic review and applications. *Multimedia Tools and Applications*, *84*(21), 23661-23700.

Shafik, W. (2025). Security, Privacy, and Ethical. *Generative Artificial Intelligence (AI) Approaches for Industrial Applications*, *93*.

Shen, L., Sun, Y., Yu, Z., Ding, L., Tian, X., & Tao, D. (2024). On efficient training of large-scale deep learning models. *ACM Computing Surveys*, *57*(3), 1-36.

Shrivastava, A., Rameshan, R., & Agnihotri, S. (2024). Latent space characterization of autoencoder variants. *arXiv preprint arXiv:2412.04755*.

Singh, S., Kumar, A., Jha, A., Jacob, N., & Mondal, M. S. (2025). AI Alignment: Ensuring AI objectives match human values. *Int. J. Sci. Res. Eng. Manag*, *9*(04), 1-9.

Sophia, L. I. (2025). The social harms of ai-generated fake news: Addressing deepfake and ai political manipulation. *Digital Society & Virtual Governance*, *1*(1), 72-88.

Spathis, D., & Kawsar, F. (2024). The first step is the hardest: Pitfalls of representing and tokenizing temporal data for large language models. *Journal of the American Medical Informatics Association*, *31*(9), 2151-2158.

Subramanian, S., Harrington, P., Keutzer, K., Bhimji, W., Morozov, D., Mahoney, M. W., & Gholami, A. (2023). Towards foundation models for scientific machine learning: Characterizing scaling and transfer behavior. *Advances in Neural Information Processing Systems*, *36*, 71242-71262.

Sun, J., Zheng, C., Xie, E., Liu, Z., Chu, R., Qiu, J., ... & Li, Z. (2025). A survey of reasoning with foundation models: Concepts, methodologies, and outlook. *ACM Computing Surveys*, *57*(11), 1-43.

Tanveer, H., Adam, M. A., Khan, M. A., Ali, M. A., & Shakoor, A. (2023). Analyzing the performance and efficiency of machine learning algorithms, such as deep learning, decision trees, or support vector machines, on various datasets and applications. *The asian bulletin of big data management*, *3*(2), 126-136.

Thaker, R. (2024). Generative AI and Robotics: From Large Language Models to Intelligent Human-Robot Interaction and Task Planning. *International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences*, *12*(4).

Thalpage, N. (2023). Unlocking the black box: Explainable artificial intelligence (XAI) for trust and transparency in ai systems. *J. Digit. Art Humanit*, *4*(1), 31-36.

Torfi, A., Shirvani, R. A., Keneshloo, Y., Tavaf, N., & Fox, E. A. (2020). Natural language processing advancements by deep learning: A survey. *arXiv preprint arXiv:2003.01200*.

Trigka, M., & Dritsas, E. (2025). The evolution of Generative AI: Trends and applications. *IEEE Access*.

Uddagiri, C., & Isunuri, B. V. (2024). Ethical and privacy challenges of generative AI. In *Generative AI: Current trends and applications* (pp. 219-244). Singapore: Springer Nature Singapore.

Vishnu Shankar, S., Naffees Gowsar, S. R., & Manjubala, M. (2025). Variational autoencoders (vaes). In *Revolution with Generative AI: Trends and Techniques* (pp. 43-64). Cham: Springer Nature Switzerland.

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., ... & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7-30.

Wang, M., Fu, W., He, X., Hao, S., & Wu, X. (2020). A survey on large-scale machine learning. *IEEE Transactions on Knowledge and Data Engineering*, *34*(6), 2574-2594.

Wu, C. J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., ... & Hazelwood, K. (2022). Sustainable ai: Environmental implications, challenges and opportunities. *Proceedings of machine learning and systems*, *4*, 795-813.

Xing, Z., Feng, Q., Chen, H., Dai, Q., Hu, H., Xu, H., ... & Jiang, Y. G. (2024). A survey on video diffusion models. *ACM Computing Surveys*, *57*(2), 1-42.

Xing, Z., Feng, Q., Chen, H., Dai, Q., Hu, H., Xu, H., ... & Jiang, Y. G. (2024). A survey on video diffusion models. *ACM Computing Surveys*, *57*(2), 1-42.

Xu, C., Jia, T., Qi, J., Cai, Z., Zhang, R., Xiong, R., ... & Xu, M. (2025). Addressing critical challenges towards a robust data system for life cycle assessment. *Nature Reviews Clean Technology*, *1*(11), 788-800.

Yan, J., & Wang, X. (2022). Unsupervised and semi-supervised learning: the next frontier in machine learning for plant systems biology. *The Plant Journal*, *111*(6), 1527-1538.

Yang, L., Zhang, Z., Song, Y., Hong, S., Xu, R., Zhao, Y., ... & Yang, M. H. (2023). Diffusion models: A comprehensive survey of methods and applications. *ACM computing surveys*, *56*(4), 1-39.

Yang, T., Mei, Y., Xu, L., Yu, H., & Chen, Y. (2024). Application of question answering systems for intelligent agriculture production and sustainable management: A review. *Resources, Conservation and Recycling*, *204*, 107497.

Yao, C., Zhan, Q., Cao, Z., Lin, Y., Li, D., Shao, Y., ... & Dong, Z. (2025). Generative ai for simulating real world dynamics applications and challenges.

Zakir, M. H., Bashir, S., Nisar, K., Ibrahim, S., Khan, N., & Khan, S. H. (2024). Navigating the legal labyrinth: Establishing copyright frameworks for AI-generated content. *Remittances Review*, *9*(1), 2515-2532.

Żelaszczyk, M., & Mańdziuk, J. (2024). Text-to-image cross-modal generation: A systematic review. *arXiv preprint arXiv:2401.11631*.

Zhang, C., Bengio, S., Hardt, M., Recht, B., & Vinyals, O. (2021). Understanding deep learning (still) requires rethinking generalization. *Communications of the ACM*, *64*(3), 107-115.

Zhang, J., Zhu, H., Wang, F., Zhao, J., Xu, Q., & Li, H. (2022). Security and privacy threats to federated learning: Issues, methods, and challenges. *Security and Communication Networks*, *2022*(1), 2886795.

ZHAO, X., LU, J., DENG, C., Zheng, C., WANG, J., CHOWDHURY, T., ... & Gu, Q. (2023). Beyond one-model-fits-all: A survey of domain specialization for large language models. *arXiv preprint arXiv*, *2305*.