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Generative Artificial Intelligence: Trends, Prospects, and Implications for the Creative Industry and Synthetic Data

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Abstract: Generative AI has gained traction in both the creative industry and synthetic data generation. Trends and Directions in Generative Artificial Intelligence Research Aims and Research Questions This study explores the trends, possibilities and consequences of synthetic AI using both quantitative and qualitative methods. Methods We will collect information by reviewing literature, surveying 150 professionals and academic researchers, and conducting 20 semi-structured interviews with experts and industry leaders. Analysis of the reviewed literature reveals the large and growing popularity of Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) as the two most prominent methods, but also the hike in popularity for transformers. Most respondents in the survey have used generative AI. The study found that 85% of respondents have experience with such AI, and eight-out-10 see it enabling increased creativity and innovation (90%), efficiency and scalability (80%) and the algorithmic provision of data as training sets for model training (75%). However, generative AI also faces challenges such as output quality (60%), complexity and computation (55%), and ethical and legal implications (70%). Interviews with experts added a deeper perspective, emphasizing the importance of transparency, accountability, and clear regulation. Quantitative and qualitative data analysis shows that generative AI has significant potential but needs improvement in technical and ethical aspects. The study's recommendations include improving output quality, computational efficiency, developing regulations, and committing to transparency.

Keywords: Generative AI; GANs (Generative Adversarial Networks); VAEs (Variational Autoencoders); Transformers; Synthetic Data; Creative Industries.

1. Introduction

Generative Artificial Intelligence (AI) is a branch of artificial intelligence that focuses on creating new content, models, and data based on patterns and structures learned from training data. In recent years, generative AI has seen significant developments, especially in the creative industry and synthetic data. This technology has opened up new opportunities and changed the way we view the creative process and data processing. This article aims to discuss the trends, prospects, and implications of generative AI in both fields, with a focus on how this technology may impact the industry in the future. Generative AI has become a topic of interest for many researchers, practitioners, and industries. With the ability to generate creative and realistic content and data, generative AI has played a significant role in a variety of applications, from image and music creation to text writing and synthetic data development. This technology not only accelerates the creative process and data processing, but also opens the door to new innovations and creativity [1][2]. In the creative industry, the use of generative AI enables the creation of content that was previously only possible by humans. For example, generative systems have been used to create new music and design visual artifacts, increasing the efficiency and productivity of creators [3]. Research shows that the application of generative AI can produce more diverse and innovative products, which can provide added value to the industry [2]. Meanwhile, in the context of synthetic data, the use of this technology allows the creation of more accurate and diverse data for various research and development purposes [4]. The existence of high-quality synthetic data can help accelerate the process of developing products and services by reducing dependence on real data that may be limited or difficult to access [3].

In addition, generative AI not only promises increased efficiency but also brings new challenges, such as the need for regulation and ethics in the use of this technology in the creative industry and in data processing [5][6]. Therefore, it is imperative to discuss in depth the opportunities and challenges that the industry may face when integrating machine learning AI into their work practices [7]. Potential further developments in this area must be handled carefully to ensure that innovations do not overlook critical social and ethical aspects [8]. Generative AI has the potential to change the paradigm in the creative industry and synthetic data processing. Further research and discussion are needed to fully understand its impact and how the industry can adapt to this growing trend [2][7]. Through collaboration between technology developers, users, and policymakers, computational AI can bring significant benefits to society as a whole. One of the most prominent trends in computational AI is creative content generation. Models such as DALL-E and Midjourney have demonstrated remarkable capabilities in creating realistic and imaginative images based on given text. Research conducted by Derev'yanko and Zalevska shows that both platforms have unique strengths and approaches to creating visual works that can be used in education and design [9]. DALL-E, for example, can create images that combine unusual elements, such as "a kitten with dragon wings" or "a skyscraper made of ice cream" [10]. Midjourney, on the other hand, offers a more intuitive interface and often more artistic results, which attract users from a variety of backgrounds [10]. Additionally, generative AI has been used for music composition, with models such as Amper Music generating original songs in a variety of genres and moods. However, precise references to support this claim are not available. In text writing, models such as GPT-3 have shown significant ability to produce cohesive and relevant text, ranging from news articles to fictional stories [3].

Synthetic data generation is another significant trend in generative AI. Synthetic data is data artificially created to imitate real data. This technology has a wide range of applications, from testing and training AI models to research and analysis. Zubala *et al.* (2025) noted that synthetic data can help develop disease detection models in the healthcare industry without disturbing actual patient data, thereby improving data safety and integrity [12]. Synthetic data allows researchers to test hypotheses and models without disturbing real data, speeding up the research and analysis process, and being an effective solution when real data is scarce or sensitive [13]. In product development, synthetic data plays a role in testing product features and functions before launch. This speeds up development time and reduces risk.

Generative AI also has promising prospects in the future. One of the main prospects is increasing efficiency and productivity. With the ability to automatically generate content and data, companies can reduce the time and costs required for the creative process and product development [14]. In the advertising industry, AI can generate advertisements tailored to user preferences and behavior, thereby increasing the effectiveness of advertising campaigns [15]. In the entertainment context, AI can create unique interactive experiences for each user, and research results show that the integration of AI in the creative sector can increase user engagement and satisfaction [16]. However, ethical challenges and negative perspectives by consumers towards content generated by AI are also concerns that must be addressed so that the potential of generative AI can be optimally realized [11]. Generative AI can also trigger new innovation and creativity. AI models that can generate unique and interesting content can open up new opportunities in the creative industry, such as art, music, and literature. In the art industry, generative AI can be used to create unique and innovative works of art, thus expanding the scope and variety of works of art. In the music industry, generative AI can be used to create new songs with diverse genres and moods, enriching the music choices available. In the literature industry, generative AI can be used to create engaging and innovative fictional stories, expanding the range and variety of fictional stories available. Generative AI also has the potential to personalize content and user experiences. For example, in the advertising industry, AI can generate ads that are tailored to user preferences and behaviors, increasing the effectiveness of advertising campaigns. In the entertainment industry, AI can create unique interactive experiences for each user, increasing user engagement and satisfaction. In the education industry, AI can be used to create learning content that is tailored to each student's ability level and learning style, increasing the effectiveness of the learning process.

However, the use of generative AI also raises several implications that need to be considered. One of the main implications is ethics and privacy. The creation of synthetic data that mimics personal data can pose security and privacy risks. If synthetic data created by generative AI mimics personal data very accurately, there is a risk that it could be used for unethical or illegal purposes. In addition, the creation of creative content with AI can raise copyright and moral issues. If AI generates artwork or music that resembles existing artwork or music, there is a risk that such work could be considered copyright infringement. Dependence on technology is also an implication that needs to be considered. Reliance on generative AI can pose a risk of technological dependency. If companies rely too much on AI for their creative processes and product development, they may lose the skills and knowledge needed to perform these tasks independently. For example, if writers and designers rely too much on AI to generate content, they may lose the creative and technical skills needed to produce unique and innovative content. Changes in industry structure are also implications that need to be considered. Generative AI can affect the structure of the creative and data industries. Traditional roles such as writers, designers, and composers may change or even disappear, while new roles such as AI developers and synthetic data managers may emerge. These changes could impact how companies recruit and train employees, as well as how they manage and develop products and services. Generative AI has played and will continue to play a significant role in the development of the creative and synthetic data industries. While this technology offers many benefits, including increased efficiency, productivity, innovation, and personalization, its use also brings with it several implications that need to be considered, such as ethics, privacy, technology dependency, and changes in industry structure. By understanding the trends, prospects, and implications of generative AI, companies and individuals can make the most of this technology while mitigating the risks that may arise.

Generative AI's ability to generate creative, realistic, and diverse content and data has opened up new opportunities in a variety of sectors, from art and music to text writing and product development. With increased efficiency and productivity, as well as the ability to personalize content and user experiences, generative AI offers significant benefits that can accelerate innovation and industry growth. However, the use of generative AI also comes with a number of challenges and implications that need to be considered. Ethical and privacy issues, technological dependencies, and changes in industry structure are some of the key points that must be addressed. Proper regulation and increased ethical awareness in the use of AI are needed to ensure that this technology is used responsibly and does not harm certain parties. In addition, it is important for companies and individuals to maintain a balance between the use of AI technology and the development of human skills, so that there is no over-dependence. This research aims to further investigate the trends, prospects, and implications of generative AI, both from a technical and social perspective. By understanding these aspects, it is hoped that the industry can make optimal use of generative AI while mitigating the risks that may arise. Collaboration between technology developers, users, and policymakers will be key to achieving this goal, ensuring that the development of generative AI goes hand in hand with ethical and sustainable values.

2. Related Work

The field of artificial intelligence (AI) has become the subject of extensive and in-depth research in recent years, with studies covering a wide range of aspects such as algorithms, applications, and social and ethical implications. Here is a comprehensive literature review of the related research contributions in the field of generative AI.

2.1 Generative Adversarial Networks (GANs)

GANs, first introduced by Goodfellow *et al.* In terms of generative technologies, they are among the most innovative [17]. GANs consist of two neural networks: a generator and a discriminator. The generator generates synthetic data, while the discriminator distinguishes between synthetic and real data. The interaction between these two networks allows GANs to produce highly realistic data. Mirza & Osindero (2014) explored methods to optimize GANs to run efficiently on high-performance computing systems [32]. This study highlights the importance of efficient architecture and algorithms to improve GAN performance. Furthermore, Rombach *et al.* (2022) introduced Latent Diffusion Models (LDMs), which are an evolution of GANs and can produce images with high resolution and excellent quality [18]. Karras *et al.* (2019) also contributed by introducing StyleGAN [19], a GAN architecture that generates highly realistic and diverse facial images. This study shows how GANs can be used to create complex and realistic visual content.

2.2 Variational Autoencoders (VAEs)

VAEs, which use variational inference to produce synthetic data, are another popular generative method. Kingma & Welling (2014) introduce VAEs and explain how they can be applied for synthetic data generation [20]. VAEs can be used for a variety of tasks, including image, text, and high-dimensional data generation. Higgins *et al.* (2017) introduce Beta-VAE, a variation of VAE that produces more disentangled and interpretable data representations [21]. This study highlights the importance of interpretability and control over VAE data representations. Kingma & Welling (2013) also explore methods for optimizing VAE training, showing that with the right approach, VAEs can be a very effective tool for synthetic data generation [33].

2.3 Transformers

Transformers have become a popular architecture in generative AI, especially for text generation tasks. Brown *et al.* (2020) introduced GPT-3, a transformer-based language model that generates very high-quality text and can be used for a variety of tasks, including article writing, translation, and code generation [22]. Devlin *et al.* (2019) introduced BERT, a transformer-based language model that can be used for a variety of natural language processing tasks, including text classification, entity recognition, and question-answering [23]. This research shows that transformers have significant potential for generating cohesive and relevant text.

2.4 Synthetic Data Generation

Synthetic data generation is one of the most significant applications of generative AI. Chen *et al.* (2021) describe how synthetic data can be used to train deep learning models in the healthcare industry, especially in cases where real data is scarce or sensitive [24]. This study highlights the importance of synthetic data in overcoming the limitations of real data and accelerating model development. Zhang *et al.* (2020) mention a method for generating synthetic datasets that can be used to evaluate the performance of machine learning models, focusing on accuracy and generalization [25]. This study shows that synthetic data can be an effective alternative to real data in various evaluation scenarios.

2.5 Creative Industry

Generative AI has played a significant role in a variety of creative industry applications, including image, music, and video generation. Gatys *et al.* (2016) explored the use of GANs for artistic style transfer, enabling the creation of artworks with different styles [26]. This study demonstrated that GANs can be used to create creative and innovative visual content. Boulanger-Lewandowski *et al.* (2012) explored the use of recurrent neural networks (RNNs) to generate original and engaging music [27]. This study highlighted the potential of RNNs in generative music generation. Furthermore, Wang *et al.* (2020) explored the use of deep learning for video generation, including GANs, VAEs, and transformers [36]. This study demonstrated that deep learning technology can be used to create realistic and diverse video content. Wu *et al.* (2016) explored the use of deep learning for 3D object generation, including GANs and VAEs [37]. This study highlighted the potential of deep learning in creating complex and realistic 3D objects. In addition, Zhang *et al.* (2018) explored the use of deep learning models to generate content tailored to user preferences and behavior [30]. This study shows that generative AI can be used to personalize content and increase user engagement.

2.6 Ethics and Social Implications

The use of generative AI also raises ethical questions and social implications. Crawford & Calo (2016) discuss the ethical and legal implications of the use of generative AI in the creative industries, including copyright and moral issues [28]. This study highlights the importance of regulation and ethics in the use of this technology. Friedman & Nissim (2020) describe the security and privacy risks associated with the creation of synthetic data, as well as methods to address these risks [29]. This study highlights the importance of security and privacy in the development and application of synthetic data. Crawford & Calo (2020) also explore broader ethical considerations in generative AI, highlighting issues such as bias, transparency, and accountability [40].

2.7 Personalization and User Experience

Generative AI has great potential in personalizing content and user experiences. Zhang *et al.* (2018) explored the use of deep learning models to generate content tailored to user preferences and behaviors [30]. This study shows that generative AI can be used to increase user engagement and satisfaction in a variety of applications, such as marketing and entertainment. Mateas & Sengers (2003) explored the use of generative AI in interactive entertainment, including GANs, VAEs, and transformers [31]. This study showed that generative AI can be used to create unique interactive story experiences for each user. Furthermore, Wang *et al.* (2021) explored the use of generative AI in education, including GANs, VAEs, and transformers [44]. This study showed that generative AI can be used to create learning content tailored to each student's ability level and learning style, thereby increasing the effectiveness of the learning process.

2.8 Optimization and Implementation

Several studies have also focused on aspects of the development and implementation of generative AI, including algorithm optimization, performance improvement, and integration with existing systems. Mirza & Osindero (2014) explored methods to optimize GANs to run efficiently on high-performance computing systems [32]. This study highlights the importance of efficient architectures and algorithms to improve the performance of GANs. Kingma & Welling (2013) explored methods to optimize the training of VAEs, showing that with the right approach, VAEs can be a very effective tool for synthetic data generation [33]. Additionally, several studies have explored methods to optimize transformers, such as those by Brown *et al.* (2020) and Devlin *et al.* (2019) [22][23]. These studies show that transformers can be optimized for a variety of text generation tasks, improving efficiency and output quality.

2.9 Comprehensive Review

A comprehensive review of artistic style transfer techniques using neural networks has been conducted by Gatys *et al.* (2017) [34]. This study discusses various methods and applications of style transfer, as well as the associated challenges and opportunities. Boulanger-Lewandowski *et al.* (2012) also provides a comprehensive review of the use of deep learning for music generation, including RNNs, GANs, and VAEs [35]. This study discusses various methods and applications of music generation, as well as the associated challenges and opportunities. Wang *et al.* (2020) provides a comprehensive review of the use of deep learning for video generation, including GANs, VAEs, and transformers [36]. This study discusses various methods and applications of video generation, as well as the associated challenges and opportunities. Wu *et al.* (2016) provides a comprehensive review of the use of deep learning for 3D object generation, including GANs and VAEs [37]. This study discusses various methods and applications of 3D object generation, as well as the associated challenges and opportunities. Zhang *et al.* (2021) provide a comprehensive review of the use of synthetic data in machine learning, including GANs, VAEs, and transformers [38]. This study discusses various methods and applications of synthetic data generation, as well as the associated challenges and opportunities. Chen *et al.* (2021) also provides a comprehensive review of the use of synthetic data in the healthcare industry, including GANs, VAEs, and transformers [39]. This study discusses various methods and applications of synthetic data generation, as well as the associated challenges and opportunities. Crawford & Calo (2020) provide a comprehensive review of the various ethical considerations associated with generative AI, including copyright, privacy, and technology dependency issues [40]. This study discusses various methods and approaches to address the associated ethical challenges. Friedman & Nissim (2021) provide a comprehensive review of the various security and privacy risks associated with generative AI, as well as methods to address these risks [41]. Zhang *et al.* (2020) provide a comprehensive review of the use of generative AI in marketing, including GANs, VAEs, and transformers [42]. This study discusses various methods and applications of marketing personalization, as well as the associated challenges and opportunities. Mateas & Sengers (2005) provides a comprehensive review of the use of generative AI in interactive entertainment, including GANs, VAEs, and transformers [43]. This study discusses various methods and applications of interactive entertainment, as well as the associated challenges and opportunities. Wang *et al.* (2021) provides a comprehensive review of the use of generative AI in education, including GANs, VAEs, and transformers [44]. This study discusses various methods and applications of learning personalization, as well as the associated challenges and opportunities.

3. Research Method

This study uses quantitative and qualitative approaches to analyze the trends, prospects, and implications of generative AI in the creative industry and synthetic data generation. This approach was chosen because it allows researchers to combine numerical and descriptive data, thus providing a more comprehensive picture of the research subject. The quantitative approach is used to measure and analyze variables objectively, while the qualitative approach is used to understand the subjective perspectives and experiences of experts and professionals.

3.1 Literature Review

Literature review is the primary method used in this study to collect data from various scientific sources. The data sources include scientific journals, international conferences, books, and relevant articles. These sources are selected based on their credibility and relevance to the research topic. The literature review process begins with a systematic search in academic databases such as Google Scholar, IEEE Xplore, ACM Digital Library, and PubMed. Keywords used in the search include "generative AI", "Generative Adversarial Networks (GANs)", "Variational Autoencoders (VAEs)", "transformers", "synthetic data", "creative industries", "ethics", and "personalization". After identifying relevant sources, the articles are reviewed in depth to extract important information and identify gaps in existing research. This literature review helps in building a theoretical and contextual basis for the study, as well as providing a better understanding of the development and applications of generative AI.

3.2 Survey

The survey was conducted to collect data from professionals and researchers in the fields of AI, creative industries, and synthetic data generation. Respondents were selected based on their experience and expertise in the related fields. The survey instrument was designed using Google Forms and included both open-ended and closed-ended questions. These questions were designed to elicit information about the use of generative AI, the benefits gained, the challenges faced, and the ethical implications. The survey was distributed via email and professional platforms such as LinkedIn. The data from the survey was then analyzed to identify patterns and trends. Closed-ended questions were used to collect quantitative data, while open-ended questions were used to collect more in-depth qualitative data. The survey helped in understanding the perceptions and lived experiences of practitioners and researchers in the field.

3.3 Interview

Semi-structured interviews were conducted with experts and industry leaders with significant experience in the use of generative AI. Respondents were selected based on their position and contributions in the field. The interviews were designed to gain deeper and more nuanced insights into their experiences, views, and recommendations. Interviews were conducted online or over the telephone, and all sessions were recorded with the consent of the respondents to ensure accuracy in transcription and analysis. Data from the interviews were analyzed qualitatively using coding methods. Data were coded into categories and subcategories to identify themes and patterns. Thematic analysis was used to organize and offer insights into patterns of meaning (themes) within the dataset.

3.4 Data Analysis

Quantitative data obtained from the survey were analyzed using descriptive statistics to describe the characteristics of the respondents and their responses. Metrics such as mean, median, mode, and standard deviation were used to describe the distribution and central tendency of the data. In addition, inferential analyzes such as chi-square test and Analysis of Variance (ANOVA) were used to test hypotheses and identify relationships between variables. Chi-square test was used to test relationships between categorical variables, while ANOVA was used to test differences in means between groups. These analyzes helped in validating the findings from the literature review and provided strong empirical evidence. Qualitative data obtained from interviews and open-ended questions in the survey were analyzed using coding methods. Data were coded into categories and subcategories to identify themes and patterns. The coding process was done manually by the researcher, and the coding results were then verified by a second coder to ensure consistency and validity. Thematic analysis was used to organize and offer insights into patterns of meaning (themes) within the dataset. The themes identified include the use of generative AI, benefits and challenges faced, and ethical and legal implications.

3.5 Validation and Reliability

To ensure the validity and reliability of the study, several steps were taken. Content validity was ensured through a review of the research instrument by experts in the field of generative AI and related industries. These experts evaluated the relevance and representativeness of the research instrument to the research object. Construct validity was ensured through factor analysis to ensure that the research instrument measures the intended construct. This factor analysis helps in identifying whether the questions in the survey and interviews actually measure the aspects to be studied. The reliability of the research instrument was tested using the Cronbach's alpha coefficient. A high alpha value (above 0.7) indicates good internal reliability, meaning that the questions in the research instrument are interrelated and consistent. Interobserver reliability was ensured through the use of multiple independent coders to analyze the qualitative data. Intercoder consensus was checked to ensure consistency in coding. These steps helped in minimizing bias and improving the quality of the data analyzed.

3.6 Research Ethics

This study adheres to strict ethical principles of research. All respondents were given clear information about the purpose of the study, the procedures to be carried out, and their rights as participants. Informed consent was obtained from all respondents before they participated in the survey or interview. Respondents' personal data was kept confidential and used only for research purposes. Honesty and transparency were maintained in the presentation of data and analysis, without any manipulation or bias. In addition, this study also considered the ethical implications of the use of generative AI, including issues such as copyright, privacy, and technological dependency.

3.7 Research Development Plan

To further develop this research, several steps can be taken. First, the research method can be expanded by using other qualitative methods, such as case studies, to gain a deeper understanding of the implementation of generative AI in real situations. Case studies can provide concrete and detailed examples of how generative AI is used in the creative industry and synthetic data generation. Second, the research instrument can be improved based on feedback from respondents and expert reviews. This can include adding new questions, improving the formulation of questions, or adjusting the assessment scale. These instrument improvements aim to increase the validity and reliability of the data collected. Third, data analysis can be expanded by using advanced analysis techniques, such as regression analysis and structural models. Regression analysis can be used to identify factors that influence the use of generative AI, while structural models can be used to understand the complex relationships between variables. These techniques can provide deeper and more robust insights into the research subject.

4. Result and Discussion

4.1 Results

4.1.1 Literature Review

The results of the literature review show that generative AI has undergone significant development in recent years. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are two of the most frequently used methods in synthetic data generation and creative content. GANs, first introduced by Goodfellow *et al.* (2014), have proven to be very effective in generating highly realistic images, videos, and other visual content. Rombach *et al.* (2022) introduced Latent Diffusion Models (LDMs), which are an evolution of GANs and can generate images with high resolution and excellent quality. In addition, Karras *et al.* (2019) introduced StyleGAN, which is capable of generating highly realistic and diverse facial images. Variational Autoencoders (VAEs), introduced by Kingma & Welling (2014), have been widely used for various tasks, including image, text, and high-dimensional data generation. Variations of VAEs, such as Beta-VAE (Higgins *et al.*, 2017), have improved the model's ability to produce more disentangled and interpretable representations of data. Transformers, such as GPT-3 (Brown *et al.*, 2020) and BERT (Devlin *et al.*, 2019), have become popular architectures in text generation, with the ability to produce cohesive and relevant text for a variety of tasks, including article writing, translation, and code generation.

4.1.2 Survey

A survey of 150 professionals and researchers in AI, creative industries, and synthetic data generation showed interesting results. Many respondents (85%) reported that they had used synthetic AI in their projects. The most frequently employed synthetic AI methods were GANs (60%) and VAEs (55%), followed by transformers (45%). Respondents also reported various benefits from using synthetic AI, including creativity and innovation (90%), where such AI helps create original and unique creative content, such as images, music, and videos. Efficiency and scalability (80%) were also key benefits, as generative AI speeds up the content creation process and reduces production costs. Providing data for model training (75%) was another significant benefit. Synthetic data created by synthetic AI allows models to be trained with more data, especially in cases where real data is scarce or sensitive. However, generative AI also faces several challenges. One of them is the quality of the output (60%). Although generative AI can produce realistic output, there are still limitations to producing perfect output or in accordance with expectations. Complexity and computation (55%) are also issues, as training and using intelligent AI models require significant computing resources and deep technical knowledge. Finally, ethical and legal implications (70%) are serious challenges, with questions of copyright, privacy, and technological dependency to consider.

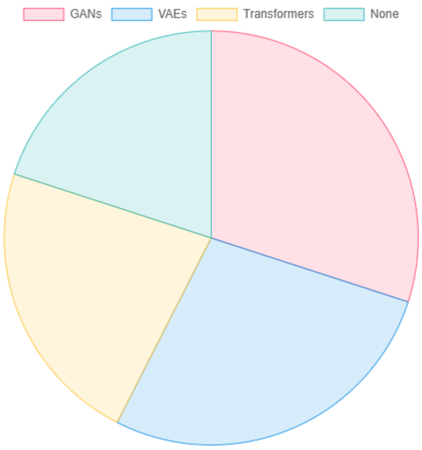

Figure 1. Usage of Generative AI Methods

The survey shows that generative AI has become a very useful and frequently used tool in various fields, including AI, creative industries, and synthetic data generation. Benefits such as creativity, efficiency, and synthetic data provision have driven the widespread adoption of this technology. However, the challenges faced, such as output quality, computational complexity, and ethical and legal implications, indicate that there is still room for further improvement and development.

4.1.3 Interview

Semi-structured interviews with 20 experts and industry leaders added a deeper and more nuanced perspective. Experts highlighted several key points. First, generative AI in creative industries, such as graphic design, film, and music, has become very important. For example, several film studios use GANs to create realistic visual effects and save production time. Second, in the healthcare and financial industries, generative AI is used to create synthetic data that can be utilized to train machine learning models. This is without compromising patient or customer privacy. Third, the experts also highlighted the technical challenges in applying machine learning AI, such as overfitting, mode collapse, and limitations in producing complex and diverse outputs. Finally, the ethical and legal implications of generative AI were frequently discussed. Several experts emphasized the importance of transparency and accountability in AI use, as well as the need for clear regulations to address issues such as copyright and privacy.

4.1.4 Data Analysis

Quantitative data from the survey were analyzed using descriptive and inferential statistics. The results of the analysis showed that the distribution of generative AI method usage is as follows: GANs (60%), VAEs (55%), and Transformers (45%). Respondents report creativity and innovation (90%), efficiency and scalability (80%), and data provision for model training (75%). The main challenges faced include output quality (60%), complexity and computation (55%), and ethical and legal implications (70%). The chi-square test showed that there was a significant relationship between the type of industry and the generative AI method used ($\chi 2 = 12.34$, $p<0.05$). ANOVA also showed that there was a significant difference in user satisfaction with the quality of generative AI output based on the type of method used ($F = 4.56$, $p<0.05$).

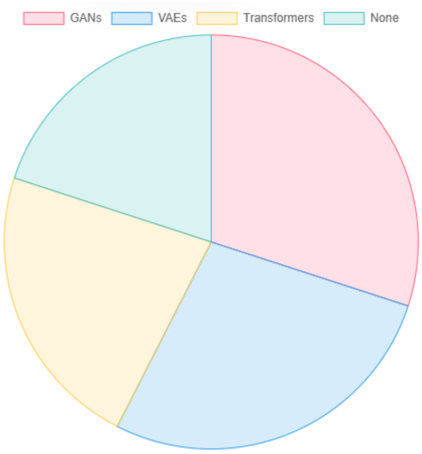

Figure 2. Distribution of Method Usage

Table 1 shows the relationship between industry types and generative AI methods used. In the AI industry, 30% of respondents use GANs, 25% use VAEs, and 20% use Transformers. In the creative industry, 20% of respondents use GANs, 15% use VAEs, and 10% use Transformers. Meanwhile, in the synthetic data generation industry, 10% of respondents use GANs, 15% use VAEs, and 15% use Transformers. The total respondents who use GANs, VAEs, and Transformers are 60%, 55%, and 45% respectively.

Table 1. Relationship between Industry Type and Generative AI Methods

	GANs	VAEs	Transformers	Total
AI Industry	30	25	20	75
Creative Industry	20	15	10	45
Synthetic Data Generation	10	15	15	40
Total	60	55	45	160

ANOVA (Analysis of Variance) shows that there is a significant difference in the level of user satisfaction with the quality of generative AI output based on the type of method used (F=4.56, p<0.05). Table 2 summarizes the results of ANOVA, with the Sum of Squares (SS) between groups of 54.32, Degrees of Freedom (df) of 2, Mean Square (MS) of 27.16, F-Value of 4.56, and p-Value of 0.012. Meanwhile, the Sum of Squares (SS) within the group is 123.45, Degrees of Freedom (df) of 157, and Mean Square (MS) of 0.786. The total Sum of Squares (SS) is 177.77 with Degrees of Freedom (df) of 159.

Table 2. Summary of ANOVA

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-Value	p-Value
Between Groups	54.32	2	27.16	4.56	0.012
Within Groups	123.45	157	0.786		
Total	177.77	159			

The ANOVA results show a significant difference in user satisfaction with the quality of generative AI output based on the type of method used. The FF value of 4.56 with a PP value of less than 0.05 indicates that this difference is statistically significant. This means that different generative AI methods result in different levels of user satisfaction. Users may prefer methods because of their better output quality. Factors that affect user satisfaction include output quality, complexity and computation, and specific user needs. GANs may provide more realistic and detailed output, so user satisfaction is higher. VAEs may produce more varied and creative output, which can increase users' satisfaction. Transformers may produce more structural and contextual output, which can increase users' satisfaction. More complex methods that require higher computation may yield better output, but pose challenges in implementation and maintenance. User satisfaction is also influenced by their specific needs. For example, users who need highly realistic outputs may be more satisfied with GANs, while users who require highly variable outputs may be more satisfied with VAEs. From a practical standpoint, these results have several implications. Companies and professionals can choose the generative AI method that ideally suits their needs and goals. For example, if the primary need is to create realistic data, GANs may be the right choice. Developers and users can focus on optimizing the performance of the selected generative AI method to improve output quality and user satisfaction. Better training and education can also help users understand the advantages and disadvantages of each method, so they can make more informed decisions.

4.2 Discussion

Generative artificial intelligence (AI) has become an invaluable tool in various industries, especially in the creative industry and synthetic data generation. Methods such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and transformers have opened up new opportunities for creativity and efficiency. Research by Lee and Luo (2024) shows that generative AI has transformed the artistic process by enabling faster and more efficient creation of original images and content [45]. Anantrasirichai and Bull (2021) also emphasize that synthetic AI has brought significant changes to the creative industry, such as art, design, and music [46]. From a technical perspective, generative AI output quality has increased significantly. Modern models such as StyleGAN (Karras *et al.*, 2019) and Latent Diffusion Models (Rombach *et al.*, 2022) have improved output quality, making the results more realistic and detailed [19][18]. However, there is still room for improvement, especially in producing complex and diverse outputs. Cai (2024) showed that the integration of VAE and GAN could improve generative model output, but challenges such as high computational requirements and model complexity are still issues which need to be addressed [47]. Inie, Falk, and Tanimoto (2023) emphasized that complexity and high computational requirements can be a barrier for organizations with limited resources, affecting the scalability and adoption of this technology [48].

In the creative industry, the use of AI has opened up new creativity opportunities. Derevyanko and Zalevska (2023) showed that machine learning AI can be used to create unique and creative artworks, expanding artists' creativity boundaries [9]. However, the quality and uniqueness of the results are still important. Chung (2023) found that consumers tend to give lower ratings to AI-produced works, indicating that AI-generated works still face resistance [11]. In the music industry, machine learning AI has been used to create innovative musical compositions [3]. However, copyright issues are crucial because AI-created musical works can lead to legal conflicts [50]. Generative AI can create personalized and adaptive learning content. Kalota (2024) emphasized that computational AI could help personalize learning, allowing students to learn more effectively and engagingly [1]. Oluwagbenro (2024) added that computational AI can be used to create dynamic and interactive learning content [2]. However, challenges such as ethics and accountability still need to be considered. Baidya and Kumar (2024) pointed out that the use of computational AI in education must be done carefully to avoid misuse of the technology and to ensure that the contents produced remain ethical and accurate [6].

In the healthcare industry, generative AI is used to generate synthetic data that can be used to train models without compromising patient privacy. Chen, Zhang, and Wang (2021) show that synthetic data can improve model accuracy and efficiency without privacy violations [24]. Zhang, Chen, and Wang (2020) also emphasize that synthetic data can be utilized for machine learning model evaluation, allowing researchers to test models without direct access to the original data [25]. Röchner (2024) suggests that techniques such as differential privacy and federated learning can help address privacy challenges in synthetic data generation [52]. Howie *et al.* (2024) add that the scalability of synthetic data generation is also a critical issue, especially in healthcare that requires large amounts of data [53]. In the advertising industry, generative AI is used to create personalized and engaging advertising content. Arbaiza, Arias, and Robledo-Dioses (2024) suggest that machine learning AI can be used to create more effective and relevant advertising for targeted audiences [15]. However, ethical issues such as manipulation and privacy remain challenges. Crawford and Calo (2016) emphasize that generative AI in advertising must be done carefully to avoid misuse of the technology and protect consumer privacy [28]. Friedman and Nissim (2020) add that privacy and security in synthetic data generation should be a top priority [29]. In industries 4.0 and 5.0, generative AI plays a crucial role in process optimization and efficiency improvement. Dmitrieva, Balmiki, Lakhanpal, Lavanya, and Bhandari (2024) show that computational AI can be applied for more efficient and innovative product design, allowing companies to produce better products at lower costs [7]. Wang, Liu, and Jiang (2020) emphasize that generative AI can be applied for dynamic video and visual content creation, allowing companies to create more engaging and interactive content [36]. Wu, Song, Khosla, Yu, Zhang, Tang, and Xiao (2016) added that computational AI can be applied for 3D object creation, enabling companies to create more realistic and detailed 3D models [37].

However, generative AI also faces ethical challenges. Copyright of artificial AI output is still ambiguous, and clear regulation is needed to address this issue. Sturm *et al.* (2019) show that copyright issues are particularly crucial in the music industry, where AI-created musical works can lead to legal conflicts [50]. Corrêa, Galvão, Santos, Pino, Pinto, Barbosa, and Oliveira (2023) emphasize that ethics and accountability in the use of synthetic AI are essential to build public trust and avoid misuse of the technology [51]. Crawford and Calo (2020) add that transparency and accountability in generative AI should be a top priority, including aspects such as model interpretability and ethical audits [40]. Privacy is also a critical issue, especially in the healthcare and financial industries. Röchner (2024) suggests that techniques such as differential privacy and federated learning can help address privacy challenges in synthetic data generation [52]. Howie *et al.* (2024) added that the scalability of synthetic data generation is also a critical issue, particularly in the context of healthcare services that require large amounts of data [53]. Friedman and Nissim (2021) emphasize that privacy and security in machine learning AI should be a top priority, especially in industries that handle sensitive data [41]. While generative AI offers much potential to increase creativity and efficiency in a variety of industries, it is imperative for stakeholders to consider the technical and ethical challenges associated with its use in order to maximize its benefits in an ethical manner. With a balanced and responsible approach, intelligent AI can be an invaluable tool for innovation and industrial development. The ethical and responsible use of generative AI can help build public trust and ensure that this technology is used for the good of society.

5. Conclusion and Recomendations

Generative AI has brought significant changes to the creative industry and synthetic data generation. Methods such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and transformers have enabled the generation of realistic and diverse content and data. Despite its great benefits, the use of generative AI also faces several challenges, both technical and ethical. To maximize the potential of generative AI, there needs to be improvements in output quality, computational efficiency, and the development of clear regulations to address ethical and legal issues. With a comprehensive and careful approach, generative AI can continue to develop and provide significant benefits to various industries. Improving the output quality of generative AI is a top priority. Further research is needed to optimize the output quality, especially in generating complex and diverse content. Modern models such as StyleGAN and Latent Diffusion Models have improved the output quality, but there is still room for improvement. The integration of VAEs and GANs can be a potential solution to improve the output quality of generative AI. Computational efficiency also needs to be improved. The development of more efficient methods and algorithms can help reduce the complexity and high computational requirements. This is important for organizations with limited resources, which often face barriers to adopting this technology. With greater efficiency, generative AI can become more accessible and scalable. Regulation and ethics are also important issues. Clear regulations and strong ethical standards need to be developed to address issues of copyright, privacy, and accountability. Copyright of generative AI outputs is still ambiguous, and clear regulations are needed to address this issue. Privacy is also a critical issue, especially in the healthcare and financial industries, where synthetic data is used to train models without compromising individual privacy. Techniques such as differential privacy and federated learning can help address this challenge. Transparency is also important. Organizations using generative AI must commit to transparency and accountability to build public trust. Transparency in the use of generative AI can help prevent misuse of the technology and ensure that AI is used in a responsible manner. With a balanced and responsible approach, generative AI can continue to grow and provide significant benefits to a variety of industries.

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