Metaheuristic Optimization Review

♦ ISSN: 2692-4048 Vol: 06, No. 02, 2026 ♦ PP. 14–18
Article DOI: https://doi.org/10.54216/MOR.060202

REVIEW ARTICLE

# The Role of GANs, VAEs, and Autoregressive Models in Neurological and Psychological Research: A Comprehensive Review

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Received: January 17, 2026 Revised: February 15, 2026 Accepted: April 15, 2026 ⋆ Corresponding author

## ABSTRACT

Generative models, including GANs, VAEs, and autoregressive models, have drastically improved neurological and psychological analyses. They allow for the formation of complex data representations that imitate cognitive processes in a human brain and thus help to understand the workings of the brain and mental diseases. Thus, GANs trained with adversarial mechanisms can synthesize nearly photorealistic fake samples, which can mimic neurological disorders or assess the effectiveness of treatment. VAEs are known to give a formidably well-founded method of learning the hidden representations of psychological states, therefore allowing researchers to study the potential causes of mental health problems. Autoregressive models, in contrast, are most applicable in time series data, which is highly important when the neurological signal or behavior under investigation needs to be studied over time. This broad survey discusses the assets and liabilities of these generative approaches, emphasizing their usability in simulating elaborate psychological processes and deploying evidence-based observations to understand the assessment and therapy of mental disorders. Therefore, this work aims to reveal the significant connections between these methodologies and their further potential for investigating human cognition and behavior through the coordinated usage of highly effective computational methods.

**Keywords:** Generative Models ▪ GANs ▪ Autoregressive Models ▪ Neuroscience ▪ Mental Health Disorders

## 1. INTRODUCTION

In recent years, artificial intelligence has undergone significant development, leading to groundbreaking innovations in fields such as neuroscience and psychology [1, 2, 3]. Among these advancements, generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and autoregressive models, are considered highly influential [4, 5]. These methods enable researchers to analyze intricate patterns that characterize complex datasets and have the potential to transform current understanding of the human brain.

The human brain is characterized by a high degree of complexity, which raises numerous scientific questions. Generative models can simulate brain-related processes and different psychological states, thereby supporting a deeper understanding of psychiatric disorders and cognitive mechanisms. These tools can help researchers reconstruct and simulate brain activity and identify possible treatments for neurological disorders [6].

Neural networks that use adversarial training, known as Generative Adversarial Networks, have become particularly important in neuroscience. By learning from high-quality data, GANs can generate samples that resemble neurological conditions and models. They have been used to examine disease development, formulate hypotheses about brain function, and evaluate the effectiveness of potential treatments.

Meanwhile, Variational Autoencoders are comparatively effective in identifying hidden representations within data. These representations are useful for analyzing concealed dynamics of psychological conditions and revealing possible patterns associated with mental diseases and disorders. By using VAEs, researchers can investigate factors associated with conditions such as depression or anxiety and define biomarkers for various psychological diseases [7].

Autoregressive models also play an important role in neurological and psychological investigations, although they serve a different function. Their primary strength lies in handling sequential or time-series data, which is particularly useful when observing behavior or neurological signals over time. By analyzing these temporal patterns, researchers can capture changes in cognition and behavior that may indicate the development or deterioration of mental health disorders.

This review examines the interaction between generative models and the fields of neuroscience and psychology. It discusses GANs, VAEs, and autoregressive models, highlighting their contributions and limitations in areas such as cognitive process simulation, diagnosis support, and treatment of mental disorders.

Furthermore, this paper addresses the potential of combining these models in research. For example, integrating the generative capabilities of GANs, the feature-learning abilities of VAEs, and the temporal analysis strengths of autoregressive models could support the development of comprehensive frameworks for studying human cognition. This potential is promising and requires further investigation [8].

This review aims to highlight the potential of high-performance computational methods in advancing neurological and psychological studies. By leveraging these methods in disease discovery, researchers may achieve significant progress in understanding the human brain. This progress may inspire new therapeutic approaches and deepen scientific comprehension of mental health [9].

However, the emergence of these models has raised important concerns regarding their ethical and practical application in neurological and psychological studies. Although generative models provide previously unavailable opportunities, their use in mental health research can involve risks. Issues such as data privacy, the reliability of synthetic data, and biases in model training must be addressed carefully. Therefore, the scientific community must establish ethical standards and develop robust validation frameworks to reduce these risks and increase confidence in the use of generative models in this field [10].

This paper analyzes the functions of GANs, VAEs, and autoregressive models in neuroscience and psychology. By reviewing case studies, applications, and current trends, the paper demonstrates their current capabilities and future potential. The insights presented here aim to support researchers and practitioners in using these tools to promote innovation in cognitive science and mental health treatment.

## 2. RELATED WORK

Due to advances in artificial intelligence, advanced generative models such as Generative Adversarial Networks, Variational Autoencoders, and autoregressive models are increasingly influencing neuroscience and psychology. These models help analyze large datasets, model cognitive processes, and improve understanding of mental health disorders. Through their distinctive characteristics, researchers can uncover hidden data patterns, study temporal dynamics, and simulate neurological and psychological conditions with high levels of authenticity. This literature review discusses the contributions, applications, and limitations of these models, as well as their future potential for advancing studies of the human brain and related disorders.

Studying the human brain is highly significant for the development of artificial intelligence, particularly in understanding visual cortex activity through functional magnetic resonance imaging (fMRI) brain signal analysis [11]. One major challenge in this area is establishing effective connectivity models from brain signals. Traditional methods often focus on voxel correlations, which represent functional rather than effective connectivity. To address this limitation, a hierarchical causality network model, known as Hcausal-Net, was proposed. This model applies Granger Causality Analysis (GCA) to stratify voxels and determine causal relationships. It effectively extracts stimulus-sensitive voxels, constructs a forward encoding process for visual perception, and improves machine-learning-based image restoration techniques.

Successful fetal cardiac bypass may enable prenatal correction of congenital heart defects, but previous studies have associated it with impaired fetal gas exchange [12]. To investigate the underlying causes, researchers examined whether fetal cardiac bypass induced redistribution of fetal regional blood flow and assessed whether sodium nitroprusside could mitigate this effect. The study evaluated blood flow in 18 fetal sheep under general anesthesia using radionuclide-labeled microspheres. The results showed a significant decrease in placental blood flow after bypass without nitroprusside, accompanied by a decline in oxygen pressure and an increase in carbon dioxide pressure. Conversely, nitroprusside improved placental blood flow, cardiac output, and arterial blood gases, suggesting that strategies enhancing placental blood flow after bypass may improve the success of fetal cardiac bypass.

Electromagnetic radiation with wavelengths between 400 and 750 nm is perceived as light by humans, with the sun serving as the primary natural source of this radiation [13]. In phenomena such as rainbows, sunlight is dispersed into its spectrum, revealing its components. Long wavelengths appear red, whereas short wavelengths appear blue-violet. Monochromatic light refers to radiation within a narrow spectral band, which is important for understanding optical properties and applications.

In recent years, the rapid development of generative artificial intelligence has significantly transformed healthcare by using large medical datasets to create new data in diverse formats, such as medical images and drug development information [14]. Techniques such as GANs, VAEs, autoregressive models, flow-based models, and probabilistic graphical models play important roles in these advancements. Applications include drug discovery, medical image enhancement, data augmentation, anomaly detection, predictive modeling, and simulation training. However, challenges remain, particularly regarding ethical and legal concerns, clinical reliability, and interpretability of AI-generated outputs in healthcare settings.

Building on major advancements in generative sampling for natural images, a novel method has been proposed to address the challenge of generating multivariate time-series samples that resemble images, particularly under limited sample-size conditions [15]. Unlike traditional deep generative models, which generate samples from a canonical distribution before decoding them to match the real data distribution, this approach uses information-theoretic principles to implicitly model the distribution of images. By estimating Kullback–Leibler divergence in its dual form with respect to marginal distributions, the method optimizes in a one-dimensional dual divergence space. Training samples are embedded into clusters between two endpoints, and generative sampling is performed through interpolation between these clusters guided by dual-function gradients. This framework improves data efficiency and reduces sample complexity for divergence estimation.

Variational Autoencoders are generative models known for learning compact and continuous latent representations of data. However, challenges arise when these representations are used for classification tasks [7]. A model called VAE-GNA was developed to address this issue by incorporating Gaussian neurons into the latent space together with attention mechanisms. These Gaussian neurons process mean and variance values using a modified sigmoid function, improving classification performance and enhancing the VAE's ability to extract features synergistically with the classification network. Both additive and multiplicative attention mechanisms were explored to further improve the model. The method was applied to automatic cancer detection using near-infrared spectral data and demonstrated superior performance compared with established baselines.

Table 1 provides an overview of the reviewed studies, focusing on studies that discuss specific uses and limitations of generative models, including GANs, VAEs, and autoregressive models in neuroscience, psychology, and related fields. The table summarizes the main contributions of each paper, including novel methods for fMRI brain signal analysis, prenatal interventions, optical property studies, healthcare applications, and generative sampling for time-series data. It also highlights the usefulness of these models in improving data effectiveness for diagnosis, developing diagnostic techniques, and identifying biomarkers for mental health problems.

In conclusion, the reviewed studies show that generative models can enhance neurological and psychological understanding. GANs, VAEs, and autoregressive models have demonstrated strong potential in replicating cognitive abilities, identifying pathologies, and creating new directions for research. However, several challenges remain, including ethical issues, data limitations, and computational constraints. The integration of these models offers a promising pathway for developing more detailed theoretical models of human cognition and behavior. Continued progress in this field may support important discoveries in mental health treatment and neurological disorder research.

Figure 1 presents the main challenges identified across the reviewed studies on generative models and their applications in neuroscience, psychology, and healthcare. The figure shows that data limitations are the most frequently reported challenge, which reflects the difficulty of obtaining large, reliable, and clinically representative datasets in sensitive domains such as brain-signal analysis and mental health research. Ethical issues, interpretability, and computational complexity also appear as major concerns, indicating that the successful use of generative models depends not only on model accuracy but also on transparency, fairness, and responsible data handling. Moreover, validation, clinical reliability, and bias remain important obstacles because AI-generated outputs must be carefully assessed before they can be trusted in research or clinical decision-making. Overall, the chart highlights that future work should focus on improving data quality, strengthening model explainability, reducing computational demands, and establishing rigorous ethical and validation frameworks.

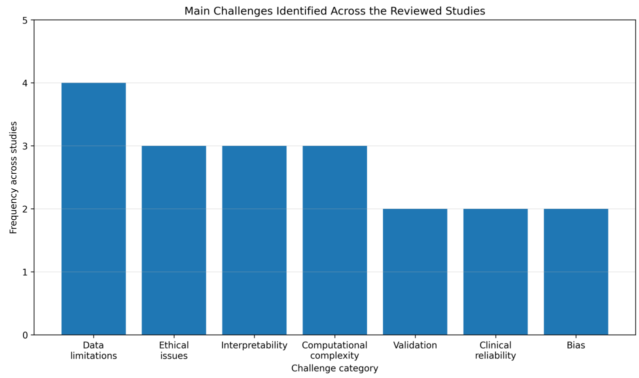


**Figure 1.** Main Challenges Identified Across the Reviewed Studies

Figure 2 illustrates the proportional distribution of the reviewed studies according to their main research focus. The chart shows that a considerable portion of the reviewed literature is categorized as related studies, which reflects the interdisciplinary nature of generative models and their connection to several domains, including healthcare, neuroscience, psychology, and signal analysis. Generative AI review studies also represent a notable proportion, indicating that recent research has placed strong emphasis on summarizing the theoretical foundations, applications, and future directions of generative artificial intelligence. Meanwhile, VAE-based studies, GAN-focused studies, healthcare AI, and brain-signal studies appear as smaller but important categories. This distribution suggests that although generative AI is increasingly discussed at a general level, more specialized empirical studies are still needed to examine its direct impact on neuroscience and psychological applications.

Figure 3 presents a model–application mapping across the reviewed studies, showing how different generative and AI-based approaches are associated with major application areas. The figure indicates that GANs, VAEs, autoregressive models, and general generative AI approaches are most strongly connected with healthcare and psychology-related applications, where they can support data generation, feature learning, classification, and simulation. Neuroscience applications are also represented, particularly through studies involving brain-signal analysis and effective connectivity modelling. The mapping further shows that time-series applications are mainly associated with autoregressive and sampling-based

**Table 1.** Summary of Literature Review

| Study Reference | Generative Model/Focus | Key Contributions | Applications | Limitations/Challenges |
|---|---|---|---|---|
| [6] | Generative Artificial Intelligence Review | Provides a systematic review of generative AI concepts, techniques, and applications across multiple domains. | General AI applications, data generation, and intelligent systems. | Requires further validation across domain-specific applications and real-world scenarios. |
| [7] | VAE-GNA Model | Introduces a variational autoencoder with Gaussian neurons in the latent space and attention mechanisms. | Classification tasks and cancer detection using near-infrared spectral data. | Needs broader testing on larger and more diverse datasets. |
| [8] | Generative AI Concepts and Future Prospects | Discusses definitions, core concepts, applications, and future prospects of generative AI. | Healthcare, education, research, and intelligent automation. | Conceptual coverage requires more empirical validation and practical case studies. |
| [9] | Generative Adversarial Networks | Reviews GAN fundamentals, variants, training challenges, applications, and open problems. | Image generation, medical imaging, simulation, and synthetic data generation. | Training instability, mode collapse, and interpretability limitations. |
| [10] | Deep Generative Modelling | Compares VAEs, GANs, normalizing flows, energy-based models, and autoregressive models. | Computer vision, representation learning, and probabilistic modelling. | Computational complexity and difficulty in selecting the most suitable model for each task. |
| [11] | Hierarchical Causality Network (Hcausal-Net) | Explores effective connectivity in brain signals using Granger Causality Analysis and machine-learning-based restoration. | fMRI brain signal analysis and visual perception. | Addressing causality and optimizing restoration techniques. |
| [12] | Fetal Cardiac Bypass Analysis | Investigates blood flow redistribution and mitigation using sodium nitroprusside. | Prenatal treatment of congenital heart defects. | Ensuring placental blood flow after bypass. |
| [13] | Electromagnetic Spectrum Study | Highlights optical properties of monochromatic light and human perception of visible light. | Understanding visual perception and optical properties. | Requires more focus on practical implications of spectrum studies. |
| [14] | Generative AI in Healthcare | Introduces GANs, VAEs, autoregressive models, and probabilistic models for medical data generation and analysis. | Drug discovery, medical imaging, anomaly detection, and simulation training. | Ethical concerns, clinical reliability, legal issues, and interpretability limitations. |
| [15] | Generative Sampling in Dual Divergence Space | Presents a KL-divergence-based method in dual space for generating multivariate time-series and image-like samples. | Image-like time-series analysis, data-efficient sampling, and real-world generative modelling. | Limited sample sizes, computational complexity, and the need to improve data efficiency. |

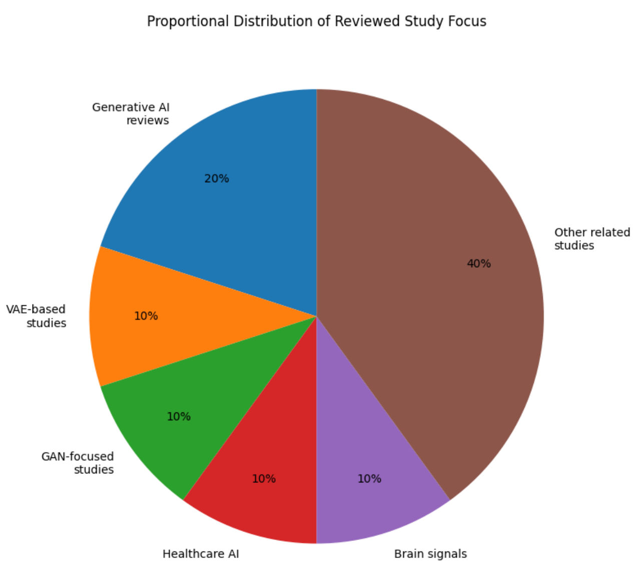


**Figure 2.** Proportional Distribution of Reviewed Study Focus

approaches, while vision-related applications are linked to studies concerned with perception and optical analysis. Overall, the figure highlights that generative models are not limited to a single research area; instead, they provide a flexible computational framework that can support multiple scientific and clinical tasks.

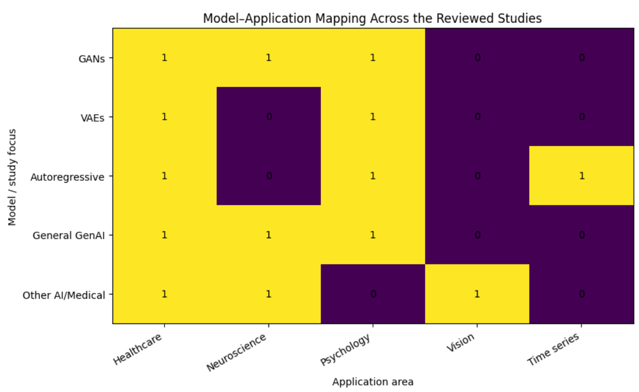


**Figure 3.** Model–Application Mapping Across the Reviewed Studies

## 3. CONCLUSION

The general development of artificial intelligence and generative models such as GANs, VAEs, and autoregressive models has provided researchers with powerful tools for addressing complex questions in neuroscience and psychology. These models have shown that artificial systems can emulate aspects of cognition, analyze complex brain-signal patterns, and detect features associated with mental and neurological diseases. Through adversarial training in GANs, feature extraction in VAEs, and temporal pattern analysis in autoregressive models, these technologies have significantly enriched the methodological foundations of the field. The studies reviewed in this paper demonstrate how these models can advance knowledge of human cognition, improve early diagnosis, and support the creation of new therapeutic strategies.

However, the use of generative models in neuroscience and psychology remains challenging despite their potential benefits. Ethical dilemmas, such as data privacy and bias in training datasets, continue to limit their wider use. In addition, extensive validation of AI-generated outputs is necessary to ensure their reliability and usefulness in clinical and research settings. Their practical application is also limited by the large amounts of data and computational power required for large-scale implementation. Addressing these challenges will be essential for expanding the use of these technologies in mental health research and practice.

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