# Variations of Architectures and Applications of Quantum Generative Adversarial Networks

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**Abstract: Generative Adversarial Networks (GANs) are generative models that function as a minimax game, in which a generative network and a discriminative network compete against each other with the goal of creating data that convincingly resembles the real sample. With the advent of Quantum Computing and the development of Quantum Machine Learning (QML) models, Quantum Generative Adversarial Networks (QuGANs) have been increasingly studied due to the possible advantages this new type of architecture can offer, especially regarding performance improvements, scalability, and the exploration of new applications. In this context, this study's guiding question is: how were QuGANs developed between the years 2018 and 2025? To answer this question, the general objective of this work is to conduct a systematic literature review of QuGANs during the proposed period. Using a systematic literature review as the methodological basis, articles published and available on the online platforms Lens, Scopus, and Web of Science were selected, and the Rayyan tool was employed to identify duplicate works and those that did not specifically address QuGANs. As a result, a prevalence of hybrid models was observed, in which the developed architecture integrates quantum and classical characteristics in a complementary manner. Regarding the type of application, approaches involving theoretical foundations and image generation stand out as the most common. Other application areas are also explored (chemistry and pharmaceuticals, quantum error correction, high-energy physics, experimental implementation, medical applications, cloud computing, anomaly detection, telecommunications, biometrics, finance, physics and simulations, security and cryptography, software engineering, noise in QuGANs, and survey), demonstrating the broad potential of QuGANs across various research fields and industrial sectors.**
**Keywords: Generative Adversarial Networks. Quantum Generative Adversarial Network. Systematic Literature Review.**
**Abbreviations: D, Discriminator. GANs, Generative Adversarial Network. G, Generator. PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses. QGANs, Quantum Generative Adversarial Networks. QML, Quantum Machine Learning.**

Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Autoregressive Networks are classifications of generative models. [1]. GANs were developed in 2014 with the aim of improving the performance of generative models through the use of backpropagation to optimize the network's weights [2].

With their cost function operating as a minimax game, the generative network **G** and the discriminative network **D** that compose GANs compete against each other, such that the training of **G** is probabilistically maximized with the goal of causing **D** to make an error, while **D** learns to distinguish whether a data sample comes from **G** or from the real data distribution [2].

The optimization process of GANs initially proposed can be represented by the equation

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right] \quad (1)$$

where $x$ is the real sample, $z$ is the random noise vector, $G(z)$ corresponds to the generated data, $\mathbb{E}$ is the expectation, $D(x)$ is the probability that **D** identifies $x$ as coming from the real data, and $D(G(z))$ indicates the probability that **D** classifies the data produced by **G** [1]. **G** and **D** are updated as the training process progresses, leading the model to a global optimal solution when $D(G(z))$ = 0,5 and **D** can no longer distinguish between the data distributions [1].

GANs resemble a Nash equilibrium, where minimizing the cost function is the objective of each player, with **D** represented by $J^{(D)}(\theta^{(D)}, \theta^{(G)})$, **G** represented by $J^{(G)}(\theta^{(D)}, \theta^{(G)})$ and the point $(\theta^{(D)}, \theta^{(G)})$ corresponding to the equilibrium reached, with $J^{(D)}$ at a minimum with respect to $\theta^{(D)}$ and $J^{(G)}$ at a minimum with respect to $\theta^{(G)}$ [3]. However, for the Nash equilibrium to be reached, failures may occur when using gradient-based cost minimization techniques, which can cause the parameters of **G** to collapse and the result to always converge to the same point [3].

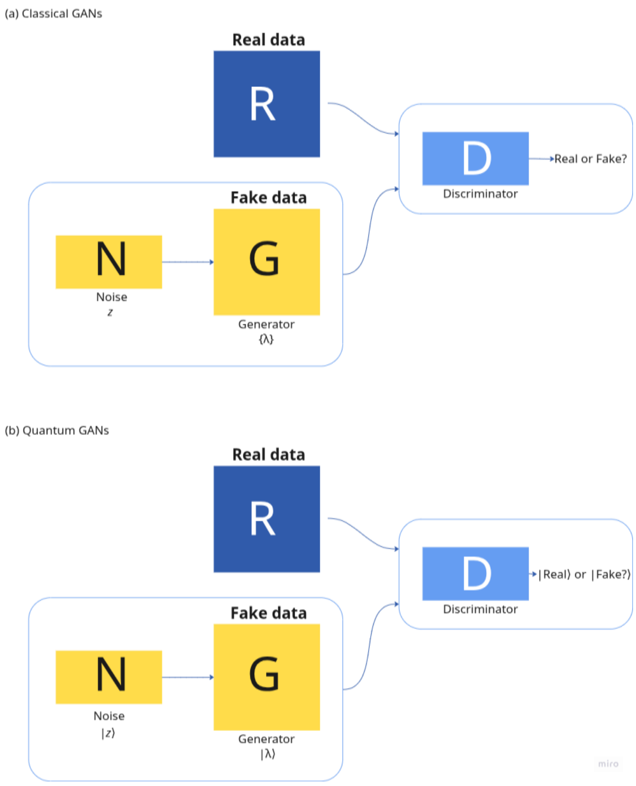
In this context, other GAN-based models have been created, optimizing their performance based on architecture (e.g., convolutional GANs, conditional GANs, and autoencoder-based GANs) and cost function (e.g., unrolled GAN, f-GAN, and WGAN) [1].

The development of Quantum Computing began in 1982 with Richard Feynman, who proposed performing computations on computers using the principles of quantum mechanics. [4]. Since then, quantum algorithms have been developed with the aim of solving problems challenging for classical binary logic, such as the Deutsch, Deutsch-Jozsa, Simon, Bernstein-Vazirani, and Shor algorithms [5].

Quantum potential, characterized by quantum speedup, highlights the fact that quantum processors can produce statistical patterns that are computationally hard to find using classical computers, giving rise to Quantum Machine Learning (QML) [6].

By introducing Quantum Generative Adversarial Networks (QuGANs), [7] show that when **G** and **D** are implemented with quantum information processors and the data correspond to measurement samples taken from high-dimensional spaces, QuGANs can demonstrate an exponential advantage compared to classical GANs. Using quantum circuits, it is possible to compute gradients and parametrize the QuGAN model, as illustrated in Figure 1 – General structure of the QuGAN, proposed by [8]. The generalization of the comparison between the classical model (GAN) and the quantum model (QuGAN) demonstrates the transformation of the network’s processing steps into quantum states, enabling advantages in the execution of the defined architecture.

**Figure 1.** General structure of the QuGAN.




Just as new research has been developed to optimize classical GANs based on architecture and cost function, the same has occurred with QuGANs, aiming to achieve better results and evaluate applications across different data segments. Therefore, this study's guiding question is: how were QuGANs developed between the years 2018 and 2025?

The general objective of this research is to conduct a systematic literature review of QuGANs during the proposed period, with specific objectives defined as: a) to extract published articles addressing QuGANs within the defined timeframe; b) to compile the types of architectures and applications of QuGANs among the selected works; and c) analyze the results based on this data.

## Materials and Methods

### Method

Following the guidelines of the PRISMA 2020 method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [9], the systematic literature review was conducted through a search for articles listed in online scientific databases, applying a filter using search terms, covering the years from 2018 to 2025, and limited to articles written in English.

### Data Collection

The material used for analysis was extracted from online scientific databases (Scopus: 75; Lens: 254; and Web of Science: 71), filtered using the search terms "quantum GAN" OR "QuGAN" OR "QGAN" OR "QGANs" OR "quantum generative adversarial network" OR "quantum generative adversarial networks." Scientific articles published between 2018 and 2025 were selected, considering the period from when the QuGANs concept was proposed until the time this research was conducted. The online platform Rayyan was used as a tool to apply exclusion criteria, enabling the identification of duplicate works and articles that did not specifically address QuGANs. After obtaining and selecting the remaining works, the software LibreOffice Calc was used to organize a spreadsheet containing the main information from each work (title, authors, abstract, keywords, publication venue, and year). Out of the 400 materials extracted from the indicated scientific databases, 81 were selected for this analysis.

**Results and Discussion**

The results related to the search for articles in the selected online databases are discussed below, demonstrating the process of selecting publications and systematically analyzing their content based on title, abstract, and keywords. The approaches of the published works are related to research on variations of QuGAN architectures (fully quantum or quantum-classical/hybrid implementations), applications in different areas, optimization processes, and specifications of quantum computing techniques used (including hardware definition for testing and implementation methods).

<u>Results of the Online Database Query</u>

Among the 400 publications, 215 duplicates were removed, leaving 265 to be analyzed. After identifying duplicate works, those that did not directly address QuGANs were also removed based on an analysis of their titles, abstracts, and keywords. From the evaluated articles, 81 were selected to identify the themes, approaches, and contributions related to the use of QuGANs. Figure 2 – Identification of publications according to the PRISMA 2020 method illustrates the process of selecting the articles deemed most suitable for conducting this analysis. The number of research studies related to QuGANs has grown since their initial proposal, indicating a trend toward new investigations over the years. Figure 3 – Number of articles per year, shows the publication count over the years, with 2025 standing out as a notable year for this topic.

**Figure 2.** Identification of publications according to the PRISMA 2020 method.

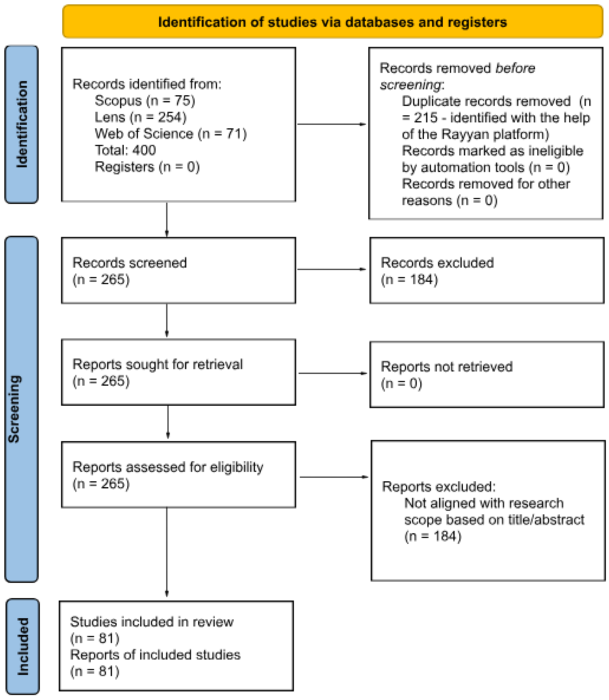
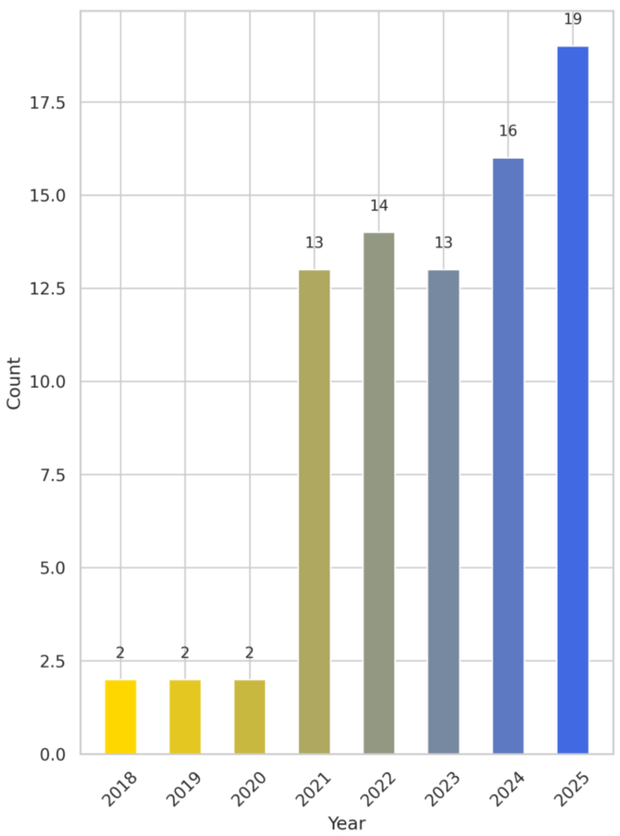


**Figure 3.** Number of articles per year.




Results of the Analyses on the Approaches of the Published Works

In relation to the identification of QuGAN architecture variations (fully quantum implementation or quantum-classical / hybrid), 53 articles reported the use of hybrid approaches [10,11,12,13,14,15,16,17,18, 19, 20, 21, 22, 23, 24,25,26,27,28,29,30,31,32,33,34,36,40,41,42,43,44,45,46,48,50,51,52,53,54,56,58,59,60,61,62, 64,66,67,68,69,70,71,73], while only 4 classified their architectures as fully quantum [35,37,38,49]. Figure 4 – Distribution by Architecture and Figure 5 – Distribution by Application Area compile the identified works, highlighting the type of architecture (fully quantum and hybrid implementations) and their application areas. Articles in the area of foundation and theorization of QuGANs stood out in the analysis [11,15,16,18,20,27,28,30,34,35,37,38,39,47,49,52,54,55,63,65,66,67,68], followed by works in the areas of image generation [13,19,26,31,32,40,60,64,70], chemistry and pharmaceuticals [12,17,22,33], quantum error correction [21,25,29,69], high-energy physics [41,51,57,61], experimental implementation [48,59,71,73], medical applications [42,44,62], cloud computing [24,56], anomaly detection [36,58], telecommunications [45,46], biometrics [10], finance [14], physics and simulations [23], security and cryptography [50], software engineering [43], noise in QuGANs [53], and surveys [72].

**Figure 4.** Distribution by Architecture.

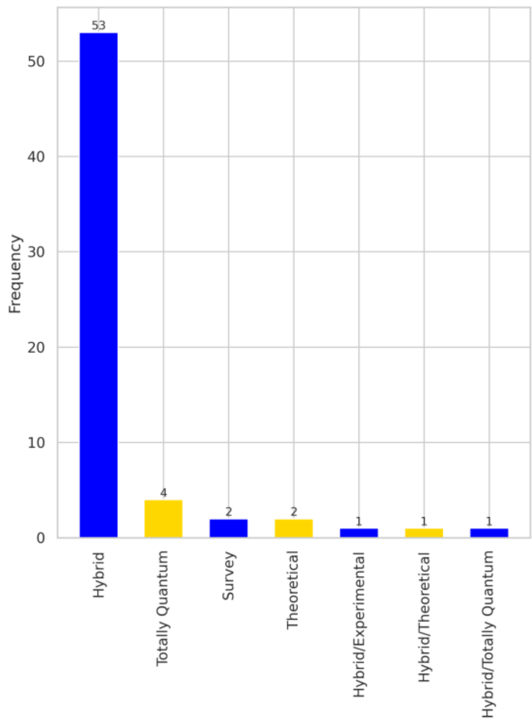
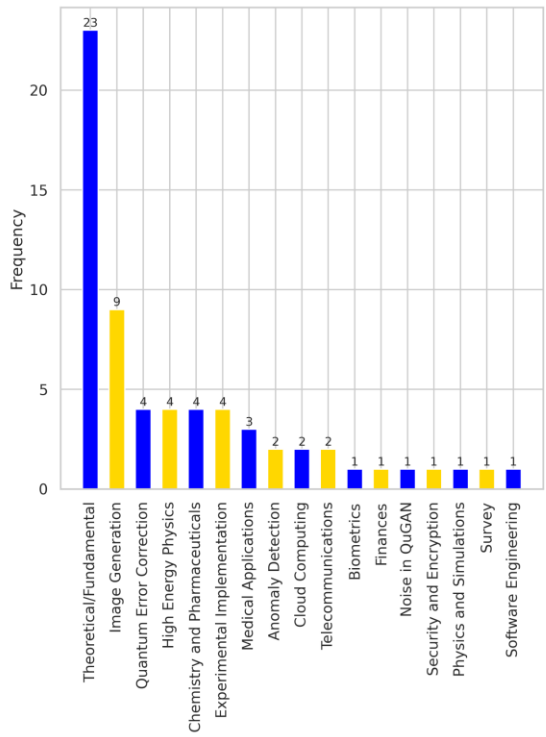


**Figure 5.** Distribution by Application Area.




## Conclusion

This study highlights how QuGANs are being researched and guides future work by revealing a predominance of hybrid architectures, applied in fields such as medicine, chemistry, finance, and security. The trend of increasing publications suggests that future analyses could group applications and architectures to better map the evolution of these networks. In 18 of the 81 articles, classification was not possible, requiring further investigation.

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