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Article

Generative Adversarial Networks in Business and Social Science

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Featured Application: The importance of generative adversarial networks (GANs) in economics is growing, driven by successes in other fields. Many economic problems could benefit from GANs, although few studies exist and progress is needed. This paper argues for the use of GANs as a novel and effective tool in economics. An important issue is the need for large data sets where traditional techniques fall short, due to the multiplicity of problems, making the use of GANs very useful in this task.

Abstract: Generative adversarial networks (GANs) have become a recent and rapidly developing research topic in Machine Learning. Since their inception in 2014, a significant number of variants have been proposed to address various topics across many fields, and has particularly excelled not only in image and language processing, but also in the medical and data science domains. In this paper, we aim to highlight the significance and advance that these GAN models can introduce in the field of Business Economics, where they have yet to be fully developed. To this end, a review of the literature of GANs is presented in general together with a more specific review in the field of Business Economics wherein only a few papers can be found. Furthermore, the most relevant papers are analysed in order to provide an approach the opportunity to research into GANs in the field of Business Economics.

Keywords: GANs; multidisciplinary application; business economics; artificial intelligence; machine learning

1. Introduction

Currently, we are facing a continuous technological advance that necessitates significant societal changes. In light of this new social structure, massive data holds particular interest, since access to this resource signifies major privileges. Traders, manufacturers, suppliers, insurers and entrepreneurs all require access to and the ability to utilise extensive databases that enable them to study and uncover the necessary information to establish commercial strategies. This access also allows them to understand customer profiles and preferences, thereby enabling informed decision-making on pricing, promotions, risk assessment, competition, business models, and more. However, these highly coveted volumes of data have surpassed human capacity for collection, storage, and analysis. Consequently, to undertake these tasks effectively, humans require suitable tools, such as statistics intelligence and machine learning.

Major advances are being made in machine learning have been utilised to recognise patterns and identify objects. However, has recently there been a leap towards generating entirely new objects and individuals.

Thus, by using two antagonistic neural networks, [1] propose a tool called "Generative Adversarial Networks" (GAN), which is capable of creating faces of people that are not real and difficult to differentiate from real faces. While this is one of the most popular applications of GANs, its true importance lies in its capability to generate synthetic data that appears indistinguishable from real data.

In this paper, a bibliographic review of GANs is conducted, which focuses on contributions made in the areas of Business and Social Science. Presently, within the literature, various reviews on

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GANs in general can be found [2–7].However, none of these specifically concentrates on the potential applications within the field of Business Economics. The objective is to showcase the potentiality of this tool within these two areas.

The rest of this paper is structured as follows: Section 2 briefly defines a GAN and how it functions. Section 3 presents a statistical study of publications on GANs gathered from the Web of Science. In Section 4, the focus is placed on GAN publications within the scope of this work: Business Economics. Section 5 details the relevance of this tool in the field of Business Economics. Section 6 outlines the conclusions drawn.

2. Generative Adversarial Networks

The main aim of GANs is the automatic generation of data. Its main difference from other generative models is that it does not directly use the distribution of real data; instead, it operates through a classifier. The generative model is random and adjusts itself step by step based on the classifier's response, continually refining until the discriminator is unable to differentiate between real and synthetic data.

In order to achieve this objective, two neural networks, namely the Generator and the Discriminator, are employed, which engage in a competitive process. The Generator produces synthetic data resembling real data, while the Discriminator endeavours to distinguish between real data and the data supplied by the Generator.

This competition between the Generator and Discriminator can be viewed through game theory as a zero-sum game since the two networks have conflicting objectives; as one network improves, the other deteriorates. Consequently, the minimax algorithm can be employed, which is a decision-making algorithm minimising the maximum loss in the game [8]. Thus, the training objective of GANs is to find the Nash equilibrium. [1] demonstrated that the Nash equilibrium is reached when the Generator produces samples indistinguishable from the training dataset, and the Discriminator can only randomly guess whether a sample is real or fake, which means the generated samples are indistinguishable to the Discriminator. When the Nash equilibrium is achieved, it is said that the network converges. In practice, GAN training is conducted using techniques not explicitly designed to find the Nash equilibrium, which may potentially lead to non-convergence [9]. At times, achieving convergence might necessitate the imposition of stringent conditions, which can be challenging to meet in practice [10–12].

The formal development of GANs is laid out below. GANs are generative models [1] that, in summary, function as follows: Initially, a vector noise is fed into a Generator model to create synthetic data. Subsequently, the generated data is mixed along with real data to feed a Discriminator model, which discriminates which data comes from the real dataset and which comes from the synthetic data generated from the Generator.

The goal of the Generator is to fool the Discriminator and the goal of the Discriminator is not to be fooled. This confrontation leads to the Generator being increasingly capable of providing synthetic data more similar to real data. The ideal solution in the GAN model is that the percentage of success of the Discriminator for the real data and synthetic data is 50%, in both cases. The structure of the GAN model for a database can be observed in Figure 1.

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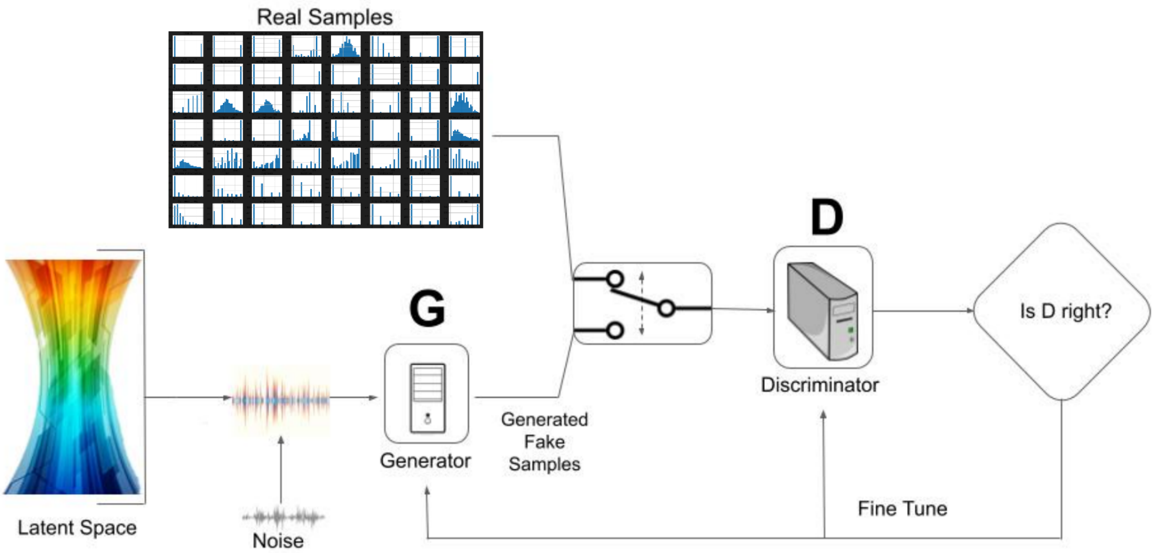

Figure 1. Structure of a Generative Adversarial Network model [13].

2.1. Mathematical Framework

Let us give a technical introduction of the GAN model: Given a database with m real samples ($\mathbf{x}$) (training data) and a random noise vector ($\mathbf{z}$), the following terms are considered:

- $G(\mathbf{z})$ is the output of the Generator from the noise $\mathbf{z}$, that is, the synthetic data.
- $D(\mathbf{x})$ is the output of the Discriminator when a real sample $\mathbf{x}$ is processed.
- $D(G(\mathbf{z}))$ is the prediction from the Discriminator on the synthetic data.
- $P_{\mathbf{x}}$ and $P_{\mathbf{z}}$ are the distribution of real and noise data, respectively.
- $E_{\mathbf{x}}$ and $E_{G(\mathbf{z})}$ are the expected log likelihoods from the different outputs of real and generated data.
- θ^D and θ^G are the weights of the Discriminator and Generator model, respectively.

The expression, denoted by V, to be considered for the complete network, Discriminator and Generator, is the following:

$$V(\theta^D, \theta^G) = E_{x \sim P_{\mathbf{x}}}[\log D(\mathbf{x})] + E_{z \sim P_{\mathbf{z}}}[\log(1 - D(G(\mathbf{z})))]. \tag{1}$$

This value function is submitted to a min–max strategy with the goal of maximising the Discriminator loss and minimising the Generator loss,

$$\min_{\theta^G} \max_{\theta^D} V(\theta^D, \theta^G). \tag{2}$$

The value for the value function V is calculated as the sum of expected log likelihood for real and synthetic samples. Maximising the resulting values leads to the optimisation of the Discriminator parameters so that it learns to correctly identify both real and fake data. To this end, the following loss functions are considered:

$$\nabla_{\theta^D} \frac{1}{m} \sum_{i=1}^{m} [\log D(\mathbf{x}^{(i)}) + \log(1 - D(G(\mathbf{z}^{(i)})))] \qquad \text{(for the Discriminator)} \tag{3}$$

$$\nabla_{\theta^G} \frac{1}{m} \sum_{i=1}^{m} \log(1 - D(G(\mathbf{z}^{(i)}))) \qquad \text{(for the Generator).} \tag{4}$$

Furthermore, a suitable setup for each artificial neuronal network employed and its training is required for the implementation of a GAN.

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2.2. Types of GANS

Both the Generator and Discriminator in GANs are neural networks; therefore, if these networks are structured to address a specific problem, then a new type of GAN is formed. The following types are worthy of note:

Conditional GAN (CGAN): This is similar to the classic GAN but allows for the generation of data from a specific class defined within the real dataset, such as the generation of MNIST digits conditioned on class labels [14].

Vanilla GAN: This is a simple type of GAN where the Discriminator and the Generator are simpler, multilayer perceptrons [1].

Deeper Convolutional GAN (DCGAN): This is a GAN where the architecture of both the generator and discriminator is composed of ConvNets instead of multilayer perceptrons [15–17].

Laplacian Pyramid GAN (LAPGAN): This combines the CGAN model with a Laplacian pyramid representation [18].

Other known networks include: SRGAN, which employs a deep neural network [19], StackGAN [20,21], CycleGAN collected in [22], PassGAN [23], WGAN in [24], Spatio-temporal GAN studied in [25], Constrained GAN which can be seen in [26], H-GAN [27], pix2pix proposed in [28], Android-GAN [29], UNIT developed in [30], RGAN and RaGAN introduced in [31], AnoGAN as proposed in [32]. [33] introduce GANomaly and RCGAN which are showcased in [34] and EGAN [35], and TimeGAN in [36], among others.

2.3. Applications of the GANs

GANs have been employed to address various types of problems, among which are:

- Generating synthetic data for training. In [37] and [13], GANs are employed to generate data related to lung cancer patients, and statistical tests are employed to validate such synthetic data. For the generation of time-series data, one can employ SeqGAN [38]. It is also possible to generate synthetic data in tabular datasets using CTGAN [39].
- Generating text and natural language. There are several notable examples: SeqGAN [38], which generates text sequences; LeakGAN [40], which introduces a search policy to enhance text generation; and RankGAN [41]. Others, like textGAN [42], are used for natural language generation. CTRL, proposed by [43], facilitates controlled text generation, and enables users to specify style and content. Additionally, GPT-3, one of the most influential studies in text generation with GAN, is based on a transformer architecture that produces high-level, coherent, and natural text [44].
- Generating realistic images. One of the initial applications of GANs in generating realistic images was introduced by [15], where they proposed a DCGAN. Subsequently, other authors suggested different GAN modalities for distinct objectives. For instance, [22] applied CycleGAN to generate images by learning domain correspondence without the need for labelled data pairs. Another example is given by [20], used StackGAN to produce detailed, high-resolution images by introducing a cascaded generator architecture. Other GAN variants, such as those employed for generating human faces [45], include StyleGAN [46–48] and BigGAN [49]. These models are utilised to enhance the quality and resolution of generated images and employ a scalable architecture. Other DCGAN variants are employed for the generation of human poses from a photograph [50] and can even project age progression of an individual [51].
- Enhancement and restoration of damaged or low-quality images. To address this issue, several alternatives to the classic GAN have been proposed, such as SRGAN [19], Pix2Pix [28] and CycleGAN [22]. The latter addresses inpainting tasks (by filling missing or damaged regions of an image) using DeepFill [52,53]. To restore images corrupted by noise, RedNet was designed [54], and for noise filtering, nCNN and FFDNet were created [55,56].

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- Speech synthesis. This constitutes one of the earliest application fields of GANs. For instance, WaveGAN was designed for waveform-based voice synthesis [57]. Similarly, MelGAN was developed for voice synthesis using high-quality Mel spectrograms, and provided enhanced quality and naturalness to synthesised voices [58]. To expedite real-time voice waveform generation, ParallelWaveGAN was proposed [59]. Other generative models include MelGAN-VC, enabling conversation [60], and HiFi-GAN for high-fidelity voice synthesis, which provides greater quality and detail [61,62]. GANs have also been used for the creation of music and songs by blending different styles and compositions of recognised musicians and composers [63].

3. Statistics on GAN Publications

In this section, the evolution of scientific articles related to GANs is presented. To this end, a search was conducted on 1 July, 2023 using the Web of Science (WOS). In the search field, the keyword used was "Generative Adversarial" or "generative adversarial" or "GENERATIVE ADVERSARIAL".

References to countries and research areas have been extracted exactly as they appear in the WOS.

The conducted search yielded a total of 18619 documents, categorised according to the type of publication, as shown in Table 1.

Table 1. Frequency per type of document.

Document Type	#	Document Type	#	Document Type	#
Articles	11168	Meeting Abstract	131	Letter	5
Proceedings	7027	Editorial Materials	21	Retracted Publication	3
Early access	503	Correction	17	Data Paper	2
Review Articles	335	Book Chapters	12	—	

In this table, we can observe that 60% of GAN publications are in the form of papers, and 38% are papers of proceedings.

Furthermore, in Table 2, the countries with the highest number of publications on this topic are displayed[1].

Table 2. Publications per countries.

Countries	#	%	Countries	#	%
China	9123	48.998	**USA**	3837	20.608
South Korea	1165	6.259	England	958	5.145
India	920	4.941	Japan	835	4.485
Germany	704	3.781	Australia	670	3.563
Canada	630	3.384	Taiwan	415	2.229
France	398	2.138	Singapore	369	1.982
Italy	350	1.880	Spain	296	1.570
Switzerland	251	1.348	Saudi Arabia	203	1.090
Others (103 countries)	3267	17.546	—	—	—

In this table, it can be observed that nearly half of all publications related to GAN originate from China, which showcases the country's positioning in emerging technologies. With just over 20%, the USA ranks second, significantly ahead of other countries.

3.1. *Evolution of GANs*

The evolution of GANs over time is depicted in Figure 2. In this figure, an estimation of publications for the year 2023 is made based on a linear fit derived from the information collected in the

[1] "Others" includes all countries with a percentage lower than 1%.

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table for previous years. The years 2014 and 2015 have not been considered in the fit, since the concept of GANs was still emerging and due to the lack of data to accurately model the real growth (as of 1/07/2023, there have been 1825 publications in the past 12 months).

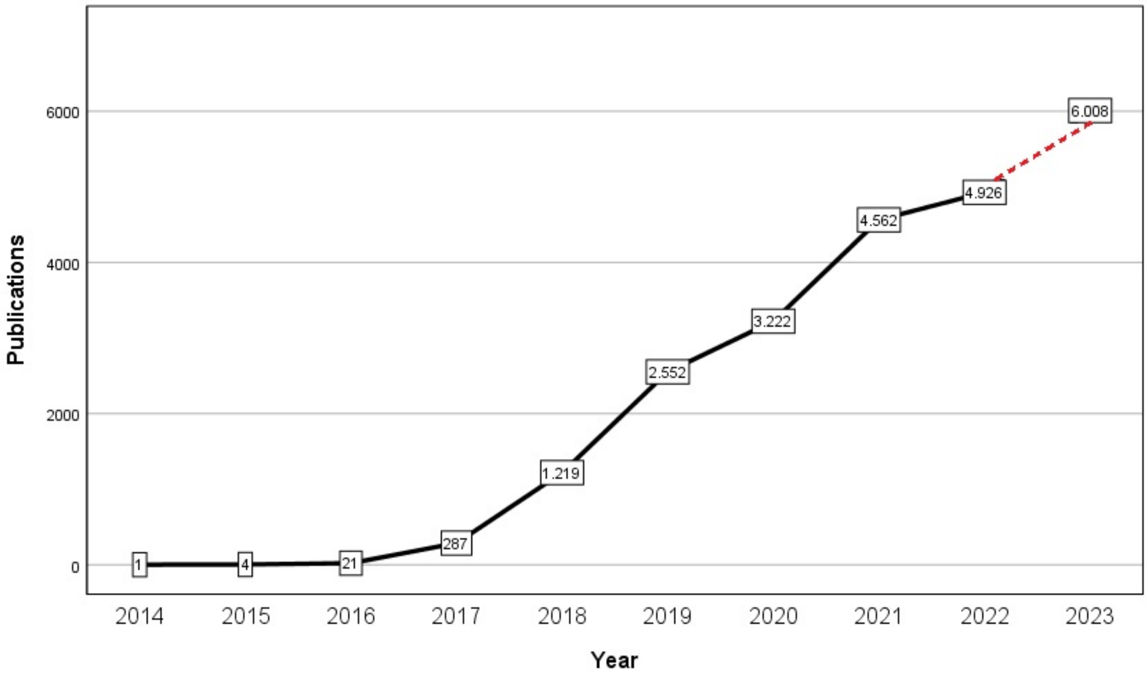

Figure 2. Number of articles published per year.

It can be observed in this figure how the growth experienced by the papers addressing GAN follows an increasing trend that has not yet reached its peak since there are still fields, such as Business and Social Sciences, where the potential provided by this GAN tool to the scientific world remains to be fully explored.

3.2. Knowledge Area and GANs

Table 3 has been obtained by taking into account the research areas collected by the WOS, and reveals the most relevant research areas (areas that reach at least 1% of all publications).

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Table 3. Publications according to research areas.

Research Areas	#	%
Computer Science	10974	58.940
Engineering	8418	45.212
Imaging Science/Photographic Technology	2368	12.718
Telecommunications	1983	10.650
Radiology/Nuclear Medicine/Medical Imaging	1182	6.348
Remote Sensing	897	4.818
Optics	868	4.662
Physics	854	4.587
Chemistry	667	3.582
Instruments/Instrumentation	674	3.620
Automation/Control Systems	631	3.389
Materials Science	507	2.723
Geology	444	2.385
Mathematics	404	2.170
Science/Technology/Other Topics	404	2.170
Mathematical/Computational Biology	389	2.089
Environmental Sciences / Ecology	361	1.939
Acoustics	351	1.885
Neurosciences/Neurology	329	1.767
Geochemistry/Geophysics	336	1.805
Robotics	283	1.520
Medical Informatics	245	1.316
Transportation	235	1.262
Energy Fuels	212	1.139
Operations Research/Management Science	189	1.015
Others (90 areas)	2283	12.261

Regarding the areas that feature a significant number of scientific publications in these GANs, the field of Computer Science stands out, encompasses a wide variety of applications in image processing, deep learning, and synthetic content generation [15,22,28,49,64].

The field of Engineering presents multiple applications, ranging from the optimisation of renewable energies to the manufacturing and monitoring of structural health, which showcases its versatility and utility in solving real-world problems [65–68].

Another field where numerous applications are found is in Imaging Science and Photographic Technology. This field is undergoing continuous evolution, for which GANs are contributing significant advancements [19,69–74]. It is a mayor challenge to enumerate the multitude of applications and problems addressed in this field that have been successfully resolved using GANs.

Work in Telecommunications also stands out [75–80].

In the field of Radiology, Nuclear Medicine and Medical Imaging, GANs appear particularly regarding the processing and analysis of medical images, improving their quality and usefulness, aiding in the diagnosis and treatment of diseases, and facilitating advancements in research [81–86].

Of great significance is the field of Remote Sensing, where GANs have contributed towards enhancing the quality and quantity of data, thereby enabling the interpretation and analysis of images, and introducing new applications and techniques for monitoring and understanding our planet from space [87–91].

GANs have overcome limitations in the field of Optics related to resolution and quality in the reconstruction of diffracted images, thereby enhancing the capacity for observation and analysis [92–94].

In the field of Physics, GANs have contributed towards significant advance in simulation techniques, data analysis, and modelling across various domains, including computational physics, particle physics, and quantum physics [95–100].

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In Chemistry, GANs have contributed towards advance in molecular techniques, drug discovery, organic synthesis, and the prediction of chemical properties, thereby opening doors to chemical and pharmaceutical research [101–104].

In the field of Instruments and Instrumentation, one can find studies applying GANs in deepfake detection, synthetic data generation, instrument calibration, and improvements in resolution in microscopy techniques [105–108].

In Automatic Control Systems, GANs have contributed innovative solutions in areas such as anomaly detection, system modelling, and synthetic data generation for the design and evaluation of control algorithms [109–114].

In Materials Science, GANs provide innovative solutions in areas such as materials discovery, molecular design, structure optimisation, and the generation of compounds with specific properties in materials science [115–118].

In Geology, several significant applications are related to facies classification techniques, geological pattern generation, image enhancement, and detection of geological features [119–122].

In Mathematics, innovative solutions have been achieved in areas such as robust optimisation, graph generation, geometric modelling, image compression, and in solving differential equations, expanding the capabilities and applications of GANs in the mathematical domain [74,123–127].

In the field of Science, Technology, and other Topics, advance have been made in image generation techniques, enhancements in the quality and stability of GANs, as well as in the manipulation and control of features in image synthesis. These advance have propelled the field of computer vision and machine learning [22,45,46,49,128].

In Mathematics Computational and Biology, advance have been made in unsupervised learning techniques, synthetic data generation, molecular modelling, and analysis of biological images, thereby opening new perspectives in mathematical and biological research [15,129,130].

The application of GANs in Environmental Sciences and Ecology has developed innovative solutions for species distribution modelling, land cover prediction, environmental data analysis, and water quality monitoring, thereby enhancing our understanding and management of ecosystems and the environment [131–133].

Also in the field of Acoustics, GANs have contributed significant solutions in areas such as audio synthesis, speech enhancement, sound simulation, and speaker verification, thereby enhancing the quality and robustness in acoustic signal processing [57,134–138].

In the field of Neurosciences and Neurology, GANs have achieved advancements in diagnostic techniques, synthetic data generation, analysis of brain signals, and the study of neurological diseases, thereby providing new insights and tools for the field of neuroscience and neurology [139–141].

When studying GANs in Geochemistry and Geophysics, significant advancements are achieved in techniques for the estimation of petrophysical properties, seismic data inversion, interpretation of geophysical data, and modelling subsurface structures. These advance enhance our understanding and analytical capabilities in exploring and characterising natural resources and geological processes [142–146].

In the field of Robotics, GANs have been applied in areas such as synthetic data generation, reinforcement learning enhancement, robotic perception, terrain classification, and robotic grasping improvement, thereby enhancing the capabilities and applications of robots in various environments and tasks [147–151].

In the field of Medical Informatics, studies on GANs have developed innovative solutions in areas such as the generation of synthetic medical images, anomaly detection, incomplete image reconstruction, and data synthesis to enhance the analysis and interpretation of medical images, thereby significantly impacting disease diagnosis and treatment [32,152–155].

In the field of Transportation, advance are made in areas such as traffic flow prediction, traffic simulation, traffic sign translation, vehicle re-identification, and estimation of public transport demand, thereby enhancing the efficiency, safety, and sustainability of transportation systems [156–160].

In the field of Energy Fuels, GANs have been applied in energy forecasting techniques, optimisation of energy systems, design of renewable energy systems, and assessment of climate-change mitigation strategies, thereby enhancing our ability to address current energy and environmental challenges [161–164].

In Operations Research and Management Science, GAN applications encompass fields such as synthetic data generation, revenue management, fraud detection, supply-chain optimisation, and dynamic pricing. These applications improve decision-making and efficiency in operations and management processes [165–168].

However, there are still significant fields where the development of such models can offer major advance and advantages that are still emerging and hold great potential in their research. One of these fields is Business Economics, where GANs can provide solutions to major problems encountered in the economic world when conducting various studies of interest. This topic is addressed in the following section.

4. Statistics on GAN Publications in Economics

In the field of Economics, GANs constitute an emerging and highly promising tool, among other things due to their ability to generate synthetic data that can help to improve economic research and analysis. Researchers often face limitations in data availability, especially when dealing with economic data. It is worth noting that having access to synthetic data in these scenarios would help simulate and predict complex economic behaviours, thereby enabling the evaluation of various economic strategies and policies well in advance to facilitate appropriate decision-making tailored to each situation.

In order to highlight these advance in the economic field and to reveal the extensive potential this tool could hold, we filter and analyse the selected bibliography, by limiting it to research directly related to this field. Hence, the number of obtained papers is reduced to a total of 42 in the the research areas considered, provided by the WOS: Bussiness Economics (29), Social Issues (3), Mathematics Methods in Social Science (7), and Social Sciences Other Topics (9).

Out of these 42 publications, we select those publications categorised as research papers, narrowing down the number to 31. In order to analyse and present these research contributions more clearly, these papers are grouped into 5 specific fields identified by the researchers: Financial Economics (9), Management (4), Marketing and Publicity (8), Logistics Transport (5), and Others (5). These areas are analysed in the following sections.

4.1. Financial Economics

The publications on GANs in the field of Financial Economics are displayed in Table 4. The first paper [169] proposes an innovative optimisation framework for the portfolio optimisation problem, by leveraging GANs to develop a heuristic approach to the classic Markowitz model. This involves three steps: i) using a GAN to select the initial set of assets for investment; ii) solving the portfolio optimisation problem to determine the weights of the assets from the previous step; and iii) enhancing the obtained solutions.

Table 4. WOS Publications in Financial Ecocomics.

Year	Title	Authors
2019	GAN-MP hybrid heuristic algorithm for non-convex portfolio optimization problem.	Kim, Y., Kang, D., Jeon, M., and Lee, C.
2020	Generative adversarial networks for financial trading strategies fine-tuning and combination.	Koshiyama, A., Firoozye, N., and Treleaven, P.
2020	A generative adversarial network approach to calibration of local stochastic volatility models.	Cuchiero, C., Khosrawi, W., and Teichmann, J.
2020	Quant GANs: deep generation of financial time series.	Wiese, M., Knobloch, R., Korn, R., and Kretschmer, P.
2021	Alleviating class imbalance in actuarial applications using generative adversarial networks.	Ngwenduna, K. S., and Mbuvha, R.
2022	Robust utility maximization under model uncertainty via a penalization approach.	Guo, I., Langrene, N., Loeper, G., and Ning, W.
2022	DeepPricing: pricing convertible bonds based on financial time-series generative adversarial networks.	Tan, X., Zhang, Z., Zhao, X., and Wang, S.
2022	Scenario generation for market risk models using generative neural networks.	Flaig, S., and Junike, G.
2022	Simulating multi-asset classes prices using Wasserstein generative adversarial network: A study of stocks, futures and cryptocurrency.	Han, F., Ma, X., and Zhang, J.

In the year 2020, [170], proposeD the use of CGAN for the calibration and aggregation of trading strategies. They designed an experiment involving multiple trading strategies across 579 assets, and yielded successful results and clear advantages over other tools.

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In [171], a data-driven approach is proposed to calibrate local stochastic volatility models using GANs, and demonstrates its feasibility and showcases several significant advantages over other methods.

An approach using a GAN-based model, referred to as Quant GAN, is introduced in [172] for modelling discrete-time financial time series. Although the models of time series have historically been notably challenging to train, advance in GANs showcase their potential to provide competitive outcomes. Thus, as training procedures continue to evolve, they hold the promise of delivering even better performance in the future.

In [173], a GAN model, named WCGAN-GP, is developed to address the challenges existing in actuarial domains, since actuaries often require a great amount of data. Furthermore, the datasets employed by actuaries frequently encounter issues with imbalanced classes, wherein events of interest related to risk are underrepresented. The authors provide several contributions to actuaries with applications including the generation of new samples, data augmentation, enhancement of predictive models, anomaly detection, and imputation of missing data.

Another paper from 2022 in the financial domain is [174], which addresses the problem of maximising utility under uncertain parameters through a robust optimisation process that can be interpreted as a stochastic differential game for two players with zero-sum. This algorithm is tested in real markets, and shows that robust portfolios tend to have higher expected utility and are more stable during market downturns. To solve the value function, the authors derive the analytical solution in the case of logarithmic utility and obtain numerical approximations using various methods, including GANs, and demonstrate a high level of accuracy in the numerical results.

It is well-known that the major complexity in valuing convertible bonds lies in modelling the underlying stock-return process. A GAN called DeepPricing that generates financial time series capable of replicating a risk-neutral stock return process while preserving statistical properties is presented in [175]. The authors declare that it is more flexible and accurate in capturing the dynamics of the underlying stock-return process.

The GANs used in [176] as generators of economic scenarios can be expanded into an entire internal market risk model, by encompassing a suitable number of risk factors. The results obtained are comparable to regulatory-approved internal models in Europe. Hence, GANs can be considered as an alternative method for market risk modelling. Furthermore, they show how a GAN can serve as an economic scenario generator for market risk calculation within insurance companies.

A Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) is given in [177], which is applied to the stock market, futures market, and cryptocurrency market. The results demonstrate that datasets generated from original asset prices by WGAN-GP simulate asset prices well, thereby showcasing the potential of a market simulator for trading analysis.

4.2. Management

All the studies in the field of Management found in the WOS are from the year 2022 and are presented in Table 5.

Table 5. WOS Publications in Management.

Year	Title	Authors
2022	Generative adversarial networks for data augmentation and transfer in credit card fraud detection.	Langevin, A., Cody, T., Adams, S., and Beling, P.
2022	A mapping the technological landscape of emerging industry value chain through a patent lens: An integrated framework with deep learning.	Xu, G., Dong, F., and Feng, J.
2022	Responsible cognitive digital clones as decision-makers:a design science research study.	Golovianko, M., Gryshko, S., Terziyan, V., and Tuunanen,T.
2022	An innovative machine learning model for supply chain management.	Lin, H., Lin, J., and Wang, F.

A study on the detection of credit-card fraud using GANs to generate synthetic samples, explicitly considering the distribution of customers, is presented in [178]. The conclusions state that using synthetically generated data has the potential to enhance model performance, and that this performance is sensitive to underlying customer distributions and data sources.

A framework is proposed in [179] to map the technological landscape of an emerging industry value chain through deep-learning-based patent analysis, by a GAN as a data augmentation method

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to overcome the issue of low-quality patent samples from the emerging industry. It is demonstrated that limitations regarding data in emerging companies and class imbalance issues can be successfully addressed.

In [180] a technology robot, called Pi-Mind, is developed and evaluated that acts as a responsible, resilient, ubiquitous cognitive clone (or a digital copy) and as an autonomous representative of a human decision-maker. To train the Pi-Mind agent to choose the most appropriate solution from among alternatives at critical decision points, they employ training agents with GANs.

The last paper in this category is by [181], who propose a method for supply chain management. To tackle the challenge of a high number of decisions and limited data samples, they propose a dynamic supply-chain-member selection algorithm based on CGAN, by previously dividing management into six areas: orders, purchases, production, inventory, distribution, and transportation.

4.3. Marketing and Publicity

Table 6 is obtained with respect to the field of Marketing and Publicity

Table 6. WOS Publications in Marketing and Publicity.

Year	Title	Authors
2021	Artificial intelligence in the fashion industry: consumer responses to generative adversarial network (GAN) technology.	Sohn, K., Sung, C. E., Koo, G., and Kwon, O.
2021	The rise of deepfakes: A conceptual framework and research agenda for marketing.	Whittaker, L., Letheren, K., and Mulcahy, R.
2022	Ad creative generation using reinforced generative adversarial network.	Terzioglu, S., Cogalmis, K. N., and Bulut, A.
2022	Preparing for an era of deepfakes and AI-generated ads: A framework for understanding responses to manipulated advertising.	Campbell, C., Plangger, K., Sands, S., and Kietzmann, J.
2022	How deepfakes and artificial intelligence could reshape the advertising industry: The coming reality of AI fakes and their potential impact on consumer behavior.	Campbell, C., Plangger, K., Sands, S., Kietzmann, J., and Bates, K.
2022	Using deep learning to overcome privacy and scalability issues in customer data transfer.	Anand, P., and Lee, C.
2023	Product aesthetic design: A machine learning augmentation.	Burnap, A., Hauser, J. R., and Timoshenko, A.
2023	Towards privacy-preserving digital marketing: an integrated framework for user modeling using deep learning on a data monetization platform.	Han, Q., Lucas, C., Aguiar, E., Macedo, P., and Wu, Z.

A comparative analysis is conducted in [182] on consumer preferences for a real fashion product versus a synthetically generated product using CycleGAN. It was observed that the creation of new designs using GAN results in a higher perceived value of the product, which potentially generates co-creation value for customers, thereby enhancing their engagement and encouraging purchasing behaviour, regardless of whether they are aware of the use of technology. The study suggests that using GAN technology can provide significant advantages by expanding the scope and scale of the product design process and by increasing perceived consumer value.

In [183], deepfakes are introduced into the marketing literature, by proposing a typology, a conceptual framework, and a research agenda based on balanced centrality. This aims to guide future research on deepfakes in marketing studies, thereby allowing both companies and customers to benefit from deepfakes while also safeguarding against potential risks.

The study presented by [184] proposes a mechanism to automate the generation of textual ad creatives, and combines a GAN model with reinforcement learning to optimise the generation of advertising texts.

Along the same lines as the aforementioned articles, [185] construct a general framework to better understand consumers' response to all forms of advertising manipulation, aided by digital and automatic tools that enable advertisers to automate many advertising processes and produce increasingly sophisticated synthetic ads. These same authors continue in their analysis of the impact that this increasingly pervasive trend of ad automation can attain. In their article, [186] show that these AI-based tools, in the same way as GANs, may bring potentially drastic changes to the way ads are conceived, produced, edited, and directed. They also examine the associated ethical issues.

Another important aspect in this field is customer privacy. [187] demonstrate that recent advance in machine learning enable companies to transfer a generative model instead of using real data. They show the effectiveness of GANs in preserving the desired characteristics of original data, which offers advantages both in terms of privacy and scalability. GANs outperform benchmark models in solving marketing problems and alleviate the logistical and computational burden for data providers, since they only need to train one GAN model that can solve various marketing problems. This approach is advantageous in terms of both volume and speed.

To influence the aesthetic design process, [188] propose a model that combines a probabilistic variational autoencoder (VAE) with adversarial components from GAN and a supervised learning

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component. The model is tested in the automotive sector and demonstrates a significant improvement compared to conventional machine learning models and neural networks.

Lastly, in this section, the work by [189] introduces an innovative approach to user modelling that preserves privacy for digital marketing campaigns by combining learning techniques and GANs. This allows users to retain control of their personal data while enabling marketing professionals to identify suitable behaviours for their campaigns.

4.4. Logistic Transport

In the field of Logistic Transport, there are several papers available (see Table 7)

Table 7. WOS Publications in Logistic Transport.

Year	Title	Authors
2020	Automated traffic incident detection with a smaller dataset based on generative adversarial networks.	Lin, Y., Li, L., Jing, H., Ran, B., and Sun, D.
2020	Coupled application of generative adversarial networks and conventional neural networks for travel mode detection using GPS data.	Li, L., Zhu, J., Zhang, H., Tan, H., Du, B., and Ran, B.
2021	A deep learning approach for real-time crash prediction using vehicle-by-vehicle data.	Basso, F., Pezoa, R., Varas, M., and Villalobos, M.
2022	Transfer learning for spatio-temporal transferability of real-time crash prediction models.	Man, C. K., Quddus, M., and Theofilatos, A.
2022	Generating mobility networks with generative adversarial networks.	Mauro, G., Luca, M., Longa, A., Lepri, B., and Pappalardo, L.

These studies address the challenge of anticipating potential accidents. However, they encounter imbalanced and limited datasets, leading to a low incident-detection rate and a high false-alarm rate in detection models. In this context, the study by [190] proposes a new incident detection framework based on GANs. Experimental results demonstrate a significant enhancement in the detection rate and a reduction in false-alarm rates.

In the paper by [191], the issue of requiring a large labelled dataset regarding travel modes to avoid congestion is addressed. Often, these travel modes are unbalanced in their representation. Hence, the authors develop a hybrid travel-mode detection model using neural networks and GANs. The GANs are employed to augment the size of the dataset and balance it, thereby enhancing the accuracy of the detection model.

On the other hand, in order to address the concern of predicting collisions in real-time, [192] propose a new data architecture inspired by images capable of capturing the microscopic scene of vehicular is constructed. For this purpose, an accident prediction model is constructed using multi-input convolutional neural networks and employ various oversampling methodologies to balance the training data. They ascertain that the best results are achieved using deep convolutional generative adversarial networks (DCGAN) with random undersampling.

The same topic is addressed in [193], but from the perspective of spatio-temporal transferability. A combination of GAN and transfer learning to examine the transferability of real-time collision prediction models in an extremely imbalanced data environment. The practical application involved using Wasserstein GAN (WGAN) to generate synthetic collision data, since the initial dataset had an extreme imbalance between collision and non-collision data. The study revealed that direct transferability is not feasible. However, the models become spatio-temporally transferable in terms of time and space, when transfer learning is applied.

The last study obtained in this field, by [194], propose a MoGAN model to generate realistic urban mobility networks. This is applied to public bicycle and taxi travel data, and demonstrates increased realism compared to classical Gravity and Radiation models. Moreover, it can be used for data augmentation, simulations, and hypothetical analyses.

4.5. Others

Finally, those studies that did not directly correspond to economics were grouped under the title "Others" (see Table 8).

Table 8. WOS Publications in the classification "Others".

Year	Title	Authors
2021	Lung-GANs: Unsupervised representation learning for lung disease classification using chest CT and X-ray images.	Yadav, P., Menon, N., Ravi, V., and Vishvanathan, S.
2022	Are deep learning models superior for missing data imputation in large surveys? Evidence from an empirical comparison.	Wang, Z., Akande, O., Poulos, J., and Li, F.
2022	Cross-lingual cybersecurity analytics in the international dark web with adversarial deep representation learning.	Ebrahimi, M., Chai, Y., Samtani, S., and Chen, H.
2023	Motion Sensor-based fall prevention for senior care: A hidden Markov model with generative adversarial network approach.	Yu, S., Chai, Y., Samtani, S., Liu, H., and Chen, H.
2023	The spiral of digital falsehood in deepfakes.	Leone, M.

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A GAN model called Lung-GAN is introduced in [195] which is trained to interpret images of lung disease to enable early diagnosis, thereby improving survival rates.

In [196], the missing-data problem is addressed due to the lack of responses in survey sampling using deep-learning models.

In [197], the use of GANs for cybersecurity analysis is proposed, which addresses the challenge of limited labelled data used by current machine-learning models trained by humans.

The aim in [198] involve fall prevention to reduce medical costs. These authors utilise a Hidden Markov Model with Generative Adversarial Networks (HMM-GAN).

In [199], the origins of deepfakes are traced back to the inception of GANs, and this phenomenon is reviewed and, presents recent statistics, prevalent application domains, risks, and opportunities. It analyses the latest bibliography, and highlighting the novelty of a scenario where falsehoods in human societies and cultures are predominantly produced by machines. This paper underscores the importance of a semiotic and interdisciplinary study of these productions.

5. Why Use GANs in Business Economics?

Given that the main aim of GANs involves the automatic generation of data, we ask as to when and how can they be used in Economics. These networks can be utilised to expand the size of the working set, since their availability in most economic problems is often scarce yet crucial. This helps in developing mechanisms essential for making economic, business, and commercial decisions, which are pivotal for the proper functioning of the sector.

On the other hand, anomaly detection is highly sought-after in this field for the detection of credit-card fraud, insurance fraud and banking operations. In these problems, there is often an imbalance issue, with only a small amount of data in the relevant class compared to abundant data in the other class. In this scenario, GANs can be conditioned to generate data for the minority class, since it is well-known that models perform better when data is balanced.

Another issue that can be addressed using GANs is that of time-series data, which can simulate temporal series and stochastic processes for risk management, financial projections, stock prediction, monetary policy formulation, price evolution, capital modelling, solvency projection, reserve management, asset and liability management, and mortality projections, among others.

Another significant issue that can be addressed by GANs is privacy preservation, given that most business data and other information may be secret, confidential, and/or sensitive. For instance, a company, such as a private hospital, could share not its real patient database but rather generate a set of synthetic data with the same characteristics as the real patients, even though these patients do not exist. This method preserves privacy while allowing the use of data to create models that improve the practices of this and other hospitals.

Another problem is that of missing data, which affects the field of business economics, and poses a challenge when applying analytical methods that are often unprepared for missing data sets.

One of the key advantages GANs offer over conventional methods in solving these aforementioned issues involves their operation through supervised learning, which enhances the performance of the models.

6. Conclusion

Throughout the numerous publications analysed, the success of the application of GANs to various problems in many diverse areas of knowledge has been demonstrated.

However, it has been shown that GANs have hitherto been underutilised in issues related to the Economic Business field.

Given the range of economic problems in which GANs can assist researchers and yield promising results, often surpassing those achieved by current techniques, we believe that GANs should be more frequently employed. GANs could offer a new perspective on several of the most current and diverse issues in this area, and could potentially provide a range of superior outcomes in many situations compared to the outcomes of existing methodologies. It has also been observed that some papers related to Economics are categorised under other areas of knowledge. For instance, [200–206] are all listed under the area of computer science. However, despite a change in these categorisations, the utilisation of GANs in economic problems still remains very limited.

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