CFS Working Paper Series

No. 713

Volker Brühl

Generative Artificial Intelligence (GAI) – foundations, use cases and economic potential

Center for Financial Studies | Goethe University | Theodor-W.-Adorno-Platz 3 | 60323 Frankfurt am Main | Germany
| Phone +49 69 798 30050 | info-cfs@hof.uni-frankfurt.de | www.gfk-cfs.de

The CFS Working Paper Series

presents ongoing research on selected topics in the fields of money, banking and finance. The papers are circulated to encourage discussion and comment. Any opinions expressed in CFS Working Papers are those of the author(s) and not of the CFS.

The Center for Financial Studies, located in Goethe University Frankfurt's House of Finance, conducts independent and internationally oriented research in important areas of Finance. It serves as a forum for dialogue between academia, policy-making institutions and the financial industry. It offers a platform for top-level fundamental research as well as applied research relevant for the financial sector in Europe. CFS is funded by the non-profit-organization Gesellschaft für Kapitalmarktforschung e.V. (GfK). Established in 1967 and closely affiliated with the University of Frankfurt, it provides a strong link between the financial community and academia. GfK members comprise major players in Germany's financial industry. The funding institutions do not give prior review to CFS publications, nor do they necessarily share the views expressed therein.

Center for Financial Studies | Goethe University | Theodor-W.-Adorno-Platz 3 | 60323 Frankfurt am Main | Germany | Phone +49 69 798 30050 | info-cfs@hof.uni-frankfurt.de | www.gfk-cfs.de

Generative Artificial Intelligence (GAI) – foundations, use cases and economic potential

Volker Brühl*

Abstract:

A key technology driving the digital transformation of the economy is artificial intelligence (AI). It has gained a high degree of public attention with the initial release of the chatbot ChatGPT, which demonstrates the potential of generative AI (GAI) as a relatively new segment within AI. It is widely expected that GAI will shape the future of many industries and society in the coming years. This article provides a brief overview of the foundations of generative AI ("GAI") including machine learning and what distinguishes it from other fields of AI. Furthermore, we look at important players in this emerging market, possible use cases and the expected economic potential as of today. It is apparent that, once again, a few US-based Big Tech firms are about to dominate this emerging technology and that the European tech sector is falling further behind. Finally, we conclude that the recently adopted Digital Markets Act (DMA) and the Digital Service Act (DSA) as well as the upcoming AI Act should be reviewed to ensure that the regulatory framework of European digital markets keeps up with the accelerated development of AI.

JEL Classification: O30, O40

*Prof. Dr. Volker Brühl, Center for Financial Studies, Goethe University, Frankfurt am Main

Generative Artificial Intelligence (GAI) – foundations, use cases and economic potential

Volker Brühl

1. Introduction

A key technology driving digital transformation is artificial intelligence (AI), which has gained a sudden momentum and a high degree of public attention with the initial release of the chatbot ChatGPT on 30 November 2022, an AI-based application developed by Open AI that anyone can use and experiment with. Despite lots of deficiencies, ChatGPT demonstrates the capabilities of an AI-based application for everybody. Within a very short period of time, ChatGPT has triggered discussions about the economic and social impact of AI and whether or not the rapid diffusion of AI technologies is desirable. Nevertheless, it is quite apparent that AI is and will continue to evolve into one of the key meta technologies that will shape the future of industry and society in the coming years if not decades.

In this article we provide a brief overview of the foundations of generative AI ("GAI") including machine learning, important players in this emerging market, possible use cases and the economic potential as of today. Finally, we draw some conclusions with regard to the role of the European tech sector and some challenges for the regulatory framework of the European regulatory sector.

2. Machine learning – a brief overview

There are a number of quite diverse definitions of the term "artificial intelligence". For instance, it may be understood as a generic term for technologies and systems with the ability to perform tasks that would otherwise require human intelligence. This presupposes certain skills that can be roughly divided into "perceiving", "reasoning/decision making", "acting" and "learning" (e.g. Russel and Nordvig, 2021). According to these basic generic elements of an AI system, AI is often divided into different fields of technologies such as "speech recognition", "image/video recognition", "natural language processing (NLP)", "computer vision" and "robotics". The perceived structured or unstructured data has to be transformed into knowledge ("knowledge representation"), forming the basis to find the optimal solution in a given environment ("knowledge reasoning and optimisation"). Performing a physical act (e.g. through actuators of robots) or providing digital information (e.g. text) usually leads to a change of the environment which may feed into a learning process of the respective AI system. Hence, a key element of AI systems is usually a type of machine learning. Machine learning (ML) is a subset of AI that seeks to enable machines to perform tasks in an optimised way through experience (Mitchell, 1997).

For instance, ML is supposed to improve decision-making, forecasting or classification problems (e.g. Murphy, 2022; Russel and Nordvig, 2021). In data science the concept of machine learning involves using statistical learning and optimisation methods that let computers analyse datasets and identify patterns (UC Berkeley, 2022).

It should be noted that ML systems do not operate on programmed solution algorithms but build a model themselves by learning from the available data. Machine learning algorithms ensure that the results of actions or changes in environmental conditions are used to optimise the system's performance in an iterative process. Hence, models based on machine learning must be trained and tested with given data sets before they can reasonably be used to draw conclusions from new data. ML is applied in many fields such as speech, image or natural language recognition. It may also be integrated into robotics, smart factories or smart home applications. Depending on the data availability and method of training, two basic learning categories – "supervised learning" and "unsupervised learning" – can be distinguished (e.g. Goodfellow et al., 2016; Mitchell, 1997; Murphy, 2022).

Supervised learning refers to the development of a prediction model that is trained with the help of given input and known output data. By comparing the model-based predictions with the correct outputs, prediction errors can be identified and the model can gradually be optimised. As the volume of training data increases, prediction errors are reduced. Learning algorithms used in the context of supervised learning include decision tree techniques, regression analysis, support vector machines (SVM), discriminant analysis and k-nearest neighbours algorithms. These algorithms can be used for tasks such as classification or forecasting. Common use cases include spam filters, fraud detection systems, recommendation engines and speech or image recognition systems. Many virtual assistants, such as Apple's Siri or Amazon's Alexa, are trained with supervised learning algorithms to communicate with users through a natural language interface.

In **unsupervised learning** settings algorithms analyse unlabelled data. The objective is to discover hidden patterns, relationships, or structures within the data. Common unsupervised learning techniques include Bayesian networks, hidden Markov models and clustering algorithms such as K-means or hierarchical clustering. Typical applications are clustering processes, e.g. for customer segmentation or in healthcare to gain a better understanding in diagnosis, prevention and treatment of diseases.

"Reinforcement learning" is a further category of machine learning in which intelligent agents attempt to optimise an output through a given incentive system. A particular form of reinforcement learning has been used in GAI by integrating human feedback during the training phase (reinforcement learning from human feedback (RLHF)).

Self-supervised learning (**SSL**) refers to a category of machine learning in which the system trains itself by first structuring the given unlabelled data, then using this structure to further optimise the output of another task. As such, this process involves transforming the unsupervised problem into a supervised problem by auto-generating the labels.

Artificial neural networks (ANN) are used as a form of machine learning, both in the field of supervised and unsupervised learning. The way that the human nervous system transmits information serves as the conceptual model for ANN. Like biological neural networks, ANNs consist of a large number of artificial neurons (units). ANNs can be classified according to various criteria, such as the number of hidden layers. Conventional ANNs contain only a few hidden layers, while so-called "deep" ANNs contain numerous hidden layers. These ANNs, also known as deep learning models, require a high volume of training data in order to achieve a satisfactory prediction quality due to the large number of connections between the neurons. Different learning algorithms are used in deep learning, such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), recurrent neural networks (RNNs), generative adversarial networks (GANs), multilayer perceptrons (MLPs), deep belief networks (DBNs) or restricted Boltzmann machines (RBMs). Artificial neural networks are now being used or tested in many different fields. These include, for example, natural language processing and speech or image recognition. Common business applications include quality management, production or sales planning, maintenance processes and credit rating systems. ANNs also play a role in research and development, e.g. in autonomous driving or biotechnology.

3. Generative AI – what sets it apart?

Generative AI is a relatively new field of AI that has gained considerable public attention, especially since the release of ChatGPT in November 2022, which is easy to use and demonstrates the power of GPT (generative pretrained transformer) systems (Cao et al., 2023). GAI is a category of AI systems that is capable of generating new text, images, videos or programming code in response to instructions ("prompts") entered by the respective user. GAI applications such as the chatbot ChatGPT (OpenAI/Microsoft) are based on the large language model (LLM) GPT-3/GPT-4. This is similar to alternative solutions including Bard (Google) that use their foundation model LaMDA. Large language models (LLMs) are deep learning networks trained on huge amounts of text data to understand the syntax and semantics of human languages in different contexts. GAI systems apply "transformer" models, which are advanced LLMs using the "attention mechanism" to help identify the most informative parts in a text by perceiving associations and meanings of words and sequences of words.

In comparison with traditional LLMs, transformers get a better and faster understanding of a task by analysing all words in a text simultaneously (rather than sequentially) while dynamically adjusting the "attention" (i.e. the perceived relevance of the word) during the solution process (Vaswani et al., 2017). The amount of training data and the number of parameters the neural network attempts to optimise are important factors for the performance of the system, for example in terms of comprehending text, generating answers to given questions, recognising images or generating code. For instance, GPT-3 is trained on 570 GB of text and can optimise up to 175 billion parameters to solve a specific task (Brown et al., 2020). Recent breakthroughs in GAI have been made possible by advances in computer hardware, especially in graphics processing units (GPUs), enabling massive parallel processing of data in machine learning models.

4. Competitive landscape and expected market potential of GAI

Figure 1 provides a brief overview of the currently important players in the field. Although the picture is only a snapshot which will certainly change in the coming years, it is striking that a substantial portion of the players belong to Big Tech companies. Most of these have their own GAI activities, but they have also added to their portfolio through acquisitions of upcoming startups in the field. Examples include the acquisition of OpenAI by Microsoft and the takeover of DeepMind by Google.

Figure 1: Important players in GAI (selection)

Use Cases	Tool	Company	Country
Chatbots	ChatGPT	OpenAI (Microsoft)	USA
	Bard	Google	USA
	Bing AI	Microsoft	USA
	HuggingChat	HuggingFace	USA
	Jasper	Jasper AI	USA
Large Language Models (LLM)	OpenAI	OpenAI (Microsoft)	USA
	Claude	Anthropic	USA
	cohere	Cohere	Canada
	LLaMA	Meta	USA
Code generation	DeepMind AlphaCode	DeepMind (Google)	USA
	GitHub Copilot	GitHub(Microsoft)	USA
	mutable.ai	MutableAI	USA
	Debuild	Debuild	USA
		Codacy	Portugal
Image/Videos	DALL·E 2	OpenAI (Microsoft)	USA
	synthesia	Synthesia	UK
		Midjourney	USA
		OpenArt	USA
	NightCafe	NightCafe Studio	Australia

Source: Own analysis

It can be expected that further takeovers of promising startups on the list will follow. This is another warning signal underlying the severe antitrust issue related to the dominant market position of Big Tech companies and their deep pockets (e.g. Brühl 2023). European companies are, with one exception, not among the important players in a field which will most likely be a major area of growth in the next decade. This becomes especially clear when we take a look at a list of important use cases that can already be identified and which covers basically all industries and many components of their value chain (Figure 2).

Figure 2: Use Cases of GAI

Modality	Use Cases (selection)	Examples
Text (ChatBots)	Customer communication	Customer care, sales, marketing
	Data Analytics	Customer segmentation, profiling
	Virtual Assistants	Sales support, technical support
	Editing	Publishing services, Translations
Image/Videos	Image recognition	Face recognition, Cyber Security Services
	Image generation	Advertising, Marketing, PR
	Video generation	Media production, PR
	Cross Media	E-commerce, E-learning
Code	Code quality check	Code audits for critical applications
	Code generation	Software development
	Code optimisation	Software engineering
	Prototyping	Product development

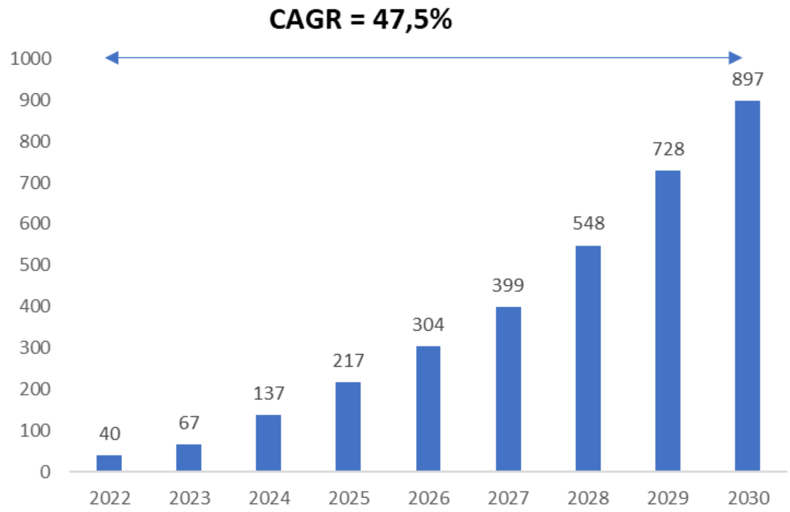
.

Source: Own analysis

At this early stage of development it is very hard to seriously estimate the future market potential of GAI as it is currently unclear how quickly new use cases will be created and how soon users will be ready to adopt them in their private or professional environment. Nevertheless, if we look at the recent publication of Bloomberg Intelligence, we see that the market has enormous expected growth (Figure 3).

The expected annual growth rate of approximately 47.5% until 2030 covers both incremental revenues from generative AI infrastructure (e.g. AI servers, AI storage solutions, computer vision and conversational AI devices) as well as specialised generative AI assistant software. Research on potential productivity enhancements through the use of GAI tools is also still at an early stage. However, a recent study by MIT researchers found that the productivity of skilled employees could be improved by up to 37% when applying chatbots such as ChatGPT in their daily writing routines (Noy and Zhang, 2023).

Figure 3: Market potential GAI until 2030



Source: Bloomberg Intelligence (2023), own calculations

5. Conclusions

Given that Europe lags behind in many areas of digital technology (e.g. AI in general, digital platforms, blockchain technology or cloud computing) it is worrying that once again the European corporate sector is about to miss out on an important digital technology. The potential risks include becoming even more dependent on the well-known Big Tech companies, as they will certainly combine GAI solutions with their existing technology franchise, e.g. as cloud providers, search engines or social media platforms. Furthermore, we have to be aware that AI in general may dramatically change our way of creating, processing and consuming content of any kind. The already unlimited potential to distribute "fake news" as well as discriminatory, racist or manipulative content will be multiplied by these new technologies. Besides, the chances of prosecuting over illegal content on social media, for example, will be significantly slimmer when the producer or owner of such harmful content is a machine. The enhanced risks of hidden plagiarism and infringements of intellectual property rights are obvious.

This is not to argue against investing heavily in these new applications of GAI, but we must not neglect the technological, social and political risks associated with them while harnessing the economic benefits. It is crucial that the regulatory framework keeps up with the accelerated development of digital technologies. Therefore, the Digital Markets Act (DMA) and the Digital Service Act (DSA) in particular, both of which were adopted in 2022, should be reviewed to ensure that they cover the recent trends in GAI. The same applies to the European "AI Act", which was published in its final draft by the European Commission as early as 2021 and is still subject to further considerations by the European authorities.

As AI becomes more advanced, humans face the challenge of comprehending how the algorithm came to a certain result. Many AI applications lack transparency of the internal calculation processes, making the generated results more or less a "black box" for the users. However, if even the data scientists who create the algorithms are not able to precisely understand and explain the AI processes applied, trust in the output and the controllability of the system is diminished. Trustworthiness and explainability of AI systems are essential features in order to establish, monitor and enforce a regulatory framework for AI. Without these characteristics, organisations cannot adopt a responsible approach to AI development that requires the system to be compliant with the regulatory standards and ensures that those affected by a decision are able to challenge or change that outcome.

Frankfurt am Main, 19 July 2023

References:

Bloomberg Intelligence (2023), Generative AI to Become a $1.3 Trillion Market by 2032, Bloomberg announcement, New York, June 1, 2023

Brown, Tom, et al. (2020), “Language models are few-shot learners.” Advances in neural information processing systems 33 (2020): 1877-1901.

Brühl, V. (2023), Big Tech, the Platform Economy and the European Digital Markets; Center for Financial Studies Working Paper No. 711, 2023

Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). A comprehensive survey of ai-generated content (aigc): A history of generative ai from gan to chatgpt. arXiv preprint arXiv:2303.04226.

Goodfellow, I., Bengio, Y., Courville, A. (2016), Deep Learning, MIT Press, Cambridge 2016

Mitchell, T.M. (1997), Machine Learning, McGraw-Hill, New York 1997

Murphy, K.P. (2022), Probabilistic Machine Learning: An Introduction (Adaptive Computation and Machine Learning series), MIT Press, Cambridge, Mass., March 2022

Noy, S., Zhang, W. (2023), Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence (March 1, 2023). Available at SSRN: https://ssrn.com/abstract=4375283 or http://dx.doi.org/10.2139/ssrn.4375283

Russel, S.J., Nordvig, P (2021), Artificial Intelligence – A Modern Approach, 4th edition, London 2021

UC Berkeley (2022), What is Machine Learning?, https://ischoolonline.berkeley.edu/blog/what-is-machine-learning/ retrieved 14/07/2023

Vaswani, Ashish, et al. (2017), “Attention is all you need.” Advances in neural information processing systems 30 (2017).

Recent Issues

All CFS Working Papers are available at *www.ifk-cfs.de*.

No.	Authors	Title
712	Isabelle Cathérine Hinsche and Rainer Klump	Mirror, Mirror on the Wall, Who Is Transitioning Amongst Them All?
711	Volker Brühl	Big Tech, the platform economy and the European digital markets
710	Andrea Zaghini	Unconventional green
709	Gilbert Fridgen, Roman Kräussl, Orestis Papageorgiou, and Alessandro Tugnetti	The Fundamental Value of Art NFTs
708	Roman Kräussl, Tobi Oladiran, and Denitsa Stefanova	ESG as Protection Against Downside Risk
707	Roman Kräussl, Joshua Pollet, and Denitsa Stefanova	Closed-end Funds and Discount Control Mechanisms
706	Roman Kräussl, Zsofia Kräussl, Joshua Pollet, and Kalle Rinne	The Performance of Marketplace Lenders
705	Rainer Haselmann, Christian Leuz, Sebastian Schreiber	Know Your Customer: Informed Trading by Banks
704	Christian Leuz, Steffen Meyer, Maximilian Muhn, Eugene F. Soltes, Andreas Hackethal	Who Falls Prey to the Wolf of Wall Street? Investor Participation in Market Manipulation
703	Christian Leuz	Towards a Design-Based Approach to Accounting Research
702	Christian Leuz, Anup Malani, Maximilian Muhn, and Laszlo Jakab	Do Conflict of Interests Disclosures Work? Evidence from Citations in Medical Journals