Defining *Generative Artificial Intelligence*

An Attempt to Resolve the Confusion about Diffusion.

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Abstract

The concept of *Generative Artificial Intelligence* (GenAI) is ubiquitous in the public domain, yet rarely defined precisely. We clarify main concepts that are usually discussed in connection to GenAI and argue that one ought to distinguish between the technical and the public discourse. In order to show its complex development and associated conceptual ambiguities, we offer a historical-systematic reconstruction of GenAI and explicitly discuss two exemplary cases: the generative status of the Large Language Model BERT and the differences between protein structure predictions from AlphaFold 2 and 3. Our analysis shows that there is no unique and unambiguous definition of GenAI based on a purely technical account of the term. Following this conclusion, we argue that the public discourse is not simply a less complex way of speaking, but instead transcends its technical basis. As a means to structure this newly emerging discussion landscape we introduce a non-exhaustive list of four central aspects of GenAI: *(multi-)modality*, *interaction*, *flexibility*, and *productivity*. These dimensions constitute a first step towards defining GenAI beyond its technical basis.

Keywords— Generative Artificial Intelligence, Generative Models, Definition of GenAI, Conceptual Analysis, History of AI, Philosophy of AI

Statements and Declarations

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1 Introduction

Since the second half of 2022 *Generative Artificial Intelligence* (GenAI) is on everyone's lips. From academic publications and discussion panels, to media coverage and opinion pieces, to funded research projects – GenAI is omnipresent. Despite this widespread interest and ubiquitous use of the term, however, there has been little attempt at a precise definition of GenAI. Rather, people are usually content to name a few exemplary systems, such as ChatGPT or Stable Diffusion, and leave the rest to implicit background knowledge and intuition. Is this because there is no need for a precise definition of GenAI or are there other reasons for this apparent conceptual vagueness? Are there any ambiguities in the discourse regarding GenAI and, if so, where do they stem from? In other words, we want to ask: *what generates the confusion about Diffusion*?

Our research question itself is the product of a long and winding road, at the beginning of which stood the idea to precisely define GenAI. As it turns out and contrary to our initial beliefs, this is not a straightforward or trivial task. There are some clear-cut exemplary cases of GenAI, such as ChatGPT or Stable Diffusion, but there is no further agreement, or even a systematic discussion of, a set of shared properties that could act as the basis of continued investigations.

The term GenAI is exclusively used in the *public* and *semi-technical* discourse and often functions as a collective term. By public and semi-technical discourse we refer to a rather broad spectrum, which ranges from popular scientific communication by journalists to researchers from other disciplines such as philosophy (see, e.g., Zohny, McMillan, and King 2023) or the social sciences (see, e.g., Bail 2024) talking about GenAI. Furthermore, it also includes communication by experts aimed at a broader audience (see, e.g., Gozalo-Brizuela and Garrido-Merchan 2023). As such, the public and semi-technical discourse comprise communication about GenAI by experts and non-experts *aimed at non-experts*. This tentative differentiation explicitly delineates the boundary between communication for a broader audience based on the term GenAI and communication for a technical, discipline-specific audience, where the term GenAI is not used. As a matter of fact, the term "Generative Artificial Intelligence" does not appear in any of the relevant technical publications that laid the foundation of the current success of GenAI – be it on Generative Adversarial Networks (GANs) (Goodfellow, Pouget-Abadie, et al. 2014), Variational Autoencoders (VAEs) (Kingma and Welling 2022), Diffusion (Sohl-Dickstein et al. 2015; Ho, Jain, and Abbeel 2020) or other models. We will refer to this mode of communication as *technical discourse*. As opposed to the public and semi-technical discourses, participants in the technical discourse do not use the term GenAI in their work, but refer exclusively to *generative models*. The exact relationship of these models to GenAI remains unclear and is not addressed in the technical literature. This suggests that there exists a discrepancy between technical and public way of speaking.

As we will argue below, the concept of GenAI is not only a simplified version to talk about generative models. On the contrary, the term GenAI transcends its technical basis and includes further, functionally relevant characteristics of certain AI-systems. By identifying a preliminary set of central aspects of GenAI, we take a crucial step towards a better understanding and set the stage for further conceptual analysis of the term. Importantly, increased clarity with respect to the concept of GenAI can have concrete and practical implications for our discussions of its potentials and limits, as well as the associated dangers. It reduces the risk of serious misunderstandings in the public domain and the attractiveness of utopian, as well as dystopian, narratives. A refined public and semi-technical discourse can in turn also positively influence the technical research of experts by enabling them to structure, relate and communicate their research more effectively.

The rest of the paper is organized as follows. In chapter 2 we elaborate the distinction between technical and public/semi-technical discourse of GenAI and establish a discussion landscape, which serves the purpose to give the reader a high level overview of and introduction to GenAI and related concepts. Since neither the technical nor the public debate is settled in itself there are changing definitions of terms, blurred boundaries and varying links between technical progress and its public perception. This is addressed in chapter 3, which gives a selective overview of the technical and conceptual history of GenAI. As the technical debate changes rapidly, partly due to innovations, there are always edge cases, two of which (BERT and AlphaFold) we will explicitly discuss in chapter 3.3. These case studies will support our argument that there are aspects of GenAI that are only insufficiently covered by a purely technical definition. In chapter 4, we propose a non-exhaustive list of four aspects that play an important role in structuring the public debate about GenAI: *(multi-)modality*, *interaction*, *flexibility*, and *productivity*. They are supposed to be a starting point for further discussions and a deeper investigation of the term GenAI. In chapter 5 we conclude our analysis of GenAI. As an outlook, we put it into context with regard to current debates in the public domain on creativity (of and with AI) and its possible consequences for the discussions on Artificial General Intelligence (AGI).

2 Discussion Landscape

In order to shed some light on the concept of GenAI and its usage, it is helpful to explain and clarify some common concepts that are often discussed in the context of GenAI and to locate where or rather *by whom* different concepts are used. As depicted in Fig. 1, the conceptual pairs we chose span a discussion landscape regarding the understanding and usage of the term GenAI.

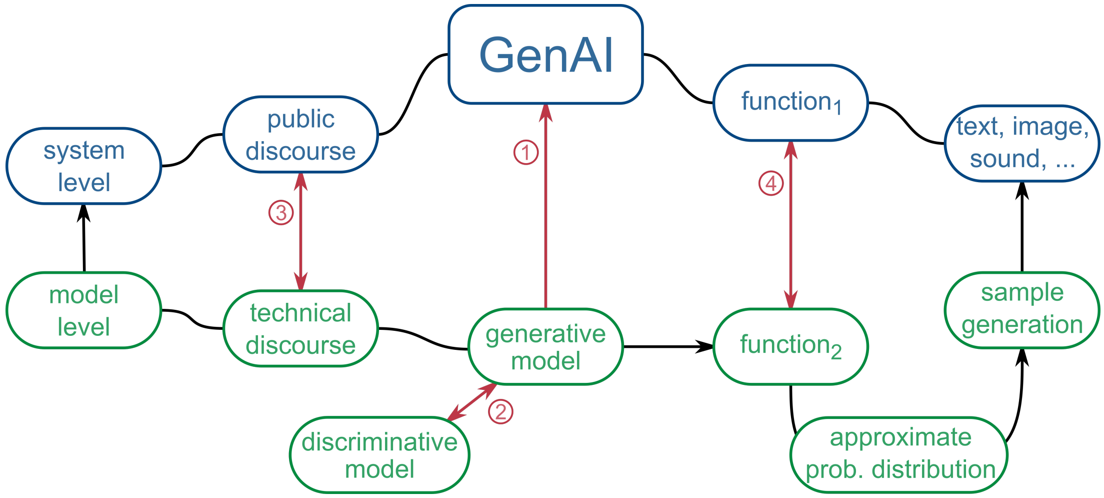

Figure 1: An overview of the current GenAI discussion landscape. The numerically labeled pairs are discussed in the continuous text.

(1) Generative AI vs. Generative Model

The first distinction we want to make is between GenAI on the one hand and generative models on the other. Technically speaking, a generative model is a statistical model that tries to approximate the underlying probability distribution given a set of data samples (observations) and can be used, in the case of GenAI, to create (*generate*) new, random instances of this learned probability distribution (Ng and Jordan 2001). In a semi-technical setting – e.g., technically informed researchers writing for a broader or interdisciplinary audience – GenAI is usually understood to somehow refer to generative models (Hacker, Engel, and Mauer 2023), but this relationship is often not specified further. Feuerriegel and colleagues define GenAI as "generative modeling that is instantiated with a machine learning architecture" and can therefore "create new data samples based on learned patterns." (Feuerriegel et al. 2024, 112)[1]

This definition attempt makes it apparent that generative modeling and GenAI are deeply intertwined, but not identical concepts – generative models are not limited to AI and have been discussed and used long before the concept of GenAI emerged, as we will explicitly discuss in chapter 3.2 below. Still, it seems that GenAI necessarily includes some generative modeling capacity in the sense that the output of such a system has to meet the same criteria as the output of a generative model – namely novelty and usefulness (Foster 2019, 10). However, as we will try to show in the following, this generative aspect is not sufficient to serve as the sole basis for a precise definition of GenAI. In fact, it is not even unambiguous on a technical level. In sum, we note that every GenAI has to produce new and useful output, but – as we will show in Chapter 3 below – the relationship to generative models is not as clear as one might think. This, in turn, necessitates our discussion of functionally relevant aspects of GenAI that cannot be reduced to a purely technical description.

(2) Generative Model vs. Discriminative Model

The distinction between generative model and discriminative model is a purely mathematical distinction of two different probabilistic models that describe different paradigms of AI research. However, this distinction is neither clear-cut nor exclusive to (generative) AI.

Discriminative models are often used for classification tasks, i.e., assigning data instances into different pre-existing categories. This includes well-known examples such as object recognition or spam detection (Sarker 2021). As the underlying probability distribution for this task is relatively easy to model, AI quickly excelled at discriminative modeling and became as ubiquitous as it is today. Generative models, in contrast, can also be used to synthesise new data instances. Since good performance by machine learning models on generative tasks strongly correlates with larger networks and training data sets,[2] it is considerably more resource intensive than

[1] Note that this is practically identical to the definition of a *Deep Generative Model* (Ruthotto and Haber 2021).

[2] In recent years, more powerful computers, increased dataset and model sizes and refined training has led to a tremendous growth of *Deep Learning* in general (Goodfellow, Bengio, and Courville 2016, 18-26).

discriminative modeling (Kaplan et al. 2020, 18-19).

In practice, "[m]any AI [models] employ both in tandem. In a generative adversarial network, for example, a generative model generates sample data and a discriminative model determines whether that data is *real* or *fake*. Output from the discriminative model is used to train the generative model until the discriminator can no longer discern 'fake' generated data." (IBM 2024) Notice that, in order to generate new data samples, a generative model also requires a probabilistic element: "If our model is merely a fixed calculation, such as taking the average value of each pixel in the dataset, it is not generative because the model produces the same output every time. The model must include a *stochastic* (random) element that influences the individual samples generated by the model." (Foster 2019, 3)

(3) Public vs. Technical Discourse

There exists a tremendous difference between the public discourse on GenAI and its technical dimension. As already mentioned above, GenAI, Generative AI or similar terms do not appear in the technical literature, but are only used in the public or semi-technical domain (e.g., in communication with other disciplines, public talks, lectures, outreach, etc.) whenever there is the need to communicate something *general* about systems such as ChatGPT or Stable Diffusion.

Table 1 depicts the main differences between public, semi-technical, and technical discourse regarding GenAI. Depending on the specific discourse, one can identify three distinct groups of participants: (1) Laypeople, who do not have any significant knowledge of GenAI; (2) Informed discourse participants with a basic understanding of GenAI and its technical basis; (3) Experts in the field of (generative) AI. Note that there can be considerable overlap between the public and semi-technical discourses, where the latter can be understood as a mediator between the public and the technical domain. While the public and semi-technical discourses both use the term GenAI, the underlying ideas are not identical. In particular, when attempting to define GenAI, informed participants typically address the model level, equating GenAI with the instantiation of a generative model. The article on regulation of LLMs by Hacker, Engel and Mauer (2023, 1113-1114) is a typical example of a contribution to the semi-technical discourse, as they try to discuss the technical foundations of GenAI models and equate GenAI with (the instantiation of) generative models. As we will show later, this narrow understanding of GenAI, based solely on its technical foundation, cannot do justice to the phenomenon at hand.

This distinction between a narrow, technical discourse and a broad, public discourse is partly mirrored by the distinction between the model level and the system level of GenAI as introduced in a recent paper by Feuerriegel and colleagues: Whereas the model level refers to the underlying technical implementation (e.g., GPT4), the system level refers to the embedding of the model functionality into a larger infrastructure (e.g., ChatGPT) (Feuerriegel et al. 2024, 112). Following this classification, we argue that the term GenAI is mostly used for functionally relevant discussions at a system level as part of the public discourse. These discussions are only occasionally tied back to technical features at the model level in the semi-technical discourse.

Discourse	**Participants**	**Usage of "GenAI"**
Public	Laypeople, Informed, Experts	Only system-level functionality is addressed, no reference to technical basis
Semi-technical	Informed, Experts	System-level and model-level can be addressed, definition of "GenAI" in terms of generative models
Technical	Experts	Only model-level is addressed, no usage of "GenAI"

Table 1: Distinction between public, semi-technical, and technical discourse regarding GenAI.

According to Google Trends (2024), search volume for the term "generative AI" only really started in the second half of 2022 – around the same time ChatGPT and Stable Diffusion were launched and created a huge public debate about the capabilities of these systems. As we will show in chapter 3, their technical basis – namely generative models instantiated with a machine learning architecture – has been around long before that. But in contrast to today, there was simply no need for a term to communicate a larger group of such models. In other words, it was only due to the performance progress in relevant functionality for broader audiences that made the term GenAI necessary for conveying the corresponding concept in the public domain.

(4) Functions of GenAI vs. Functions of Generative Models

As mentioned above, the terms GenAI and generative model are closely connected. Both terms describe applications that (ultimately) produce new data points of textual, visual, auditory, ... data. However, the *generative* function that both terms fulfil is a very different one. In the public discourse, *generative* in Generative AI refers to the generation of new text, images, sounds, or similar modalities (see, e.g., Gartner 2024; Coursera 2024; Fruhlinger 2023) and GenAI is thus often characterized by means of its system level functionality: "Often, Generative AI models are marked by their wider scope and greater autonomy in extracting patterns within large datasets. In particular, LLMs' capability for smooth general scalability enables them to generate content by processing a varying range of input from several domains." (Novelli et al. 2024, 2)

The term *generative* in generative model on the other hand refers to its function of describing "how a dataset is generated, in terms of a probabilistic model. By sampling from this model, we are able to generate new data." (Foster 2019, 2) The result of a generative model (by sampling) is typically a new data instance which ties it to *generative* of GenAI, but only indirectly and not necessarily (see also point (2) above).

The above description of the current discussion landscape on GenAI points to an important facet that should be kept in mind for the following analysis. There are two mechanisms of definition at work in the debate, referring to the *public* and the *technical* discourse. They are different in various respects, but they have complex interrelationships. In what follows, we will not simply take the position that the technical and public debates about GenAI are not identical, which would be a trivial statement. Rather, we argue that (1) the technical definition of GenAI is less clear and less unambiguous than one might think, and (2) that the public debate is not just an informal or less complex way of speaking, but that it actually transcends its technical basis regarding certain aspects. *It is one goal of this paper to offer a non-exhaustive list of aspects of GenAI that are central to the public debate, yet not captured by a purely technical discourse.*

To clarify this point, consider the following analogy: There is considerable public interest in the theory of general relativity (GR), as it is concerned with the evolution of the universe and our cosmological fate. It is good practice in introductory lectures or public talks to demonstrate certain characteristics of this theory – e.g., the curvature of space-time induced by the stress-energy tensor of an object – by invoking the image of a massive sphere on a rubber sheet. This is an attempt to visualize an important feature of GR and to convey a basic understanding of some of its important properties to laypeople (Regt 2017, 91, 114). Even though this visualisation features a dramatically reduced complexity and some necessary errors and inaccuracies, it is still firmly rooted in the technical discourse. On the other hand, consider cosmological models based on GR implying that the universe is of finite age and started from an incredibly dense, primordial state which expanded subsequently. The theory does not allow one to make any statements about space-time *before* this so-called Big Bang – in fact, this expression in itself is meaningless. While it might be genuinely interesting to many people and even important for personal questions of meaning and worldview to consider a time before the Big Bang, GR (or the appropriate cosmological model) is silent on this topic – it is simply not in reach of the technical discourse. The public debate about GenAI, we argue, is best understood by analogy to the latter type of situation in the example above. While the technical discourse forms the basis of the public discourse, it does not touch on some relevant features of GenAI.

3 Historical-Systematic Reconstruction of GenAI

The history of GenAI can be told in many different ways. The most fruitful and interesting narratives for our intents and purposes are the conceptual and technical origins of GenAI. But even when we focus exclusively on these historical developments, no single common thread can be found. Rather, important turning points can be identified in retrospect among the many approaches, programs and ideas, on the basis of which a more or less coherent story can be told. Below, we examine those turning points in history that are most relevant to our project. The heterogeneity we describe is still present today and constitutes part of the problem that this paper attempts to resolve. The two case studies at the end of this chapter will analyse selected GenAI systems to exemplify the complexities and intricacies regarding their status as GenAI.

3.1 Technical Reconstruction

If one wants to determine the term "Generative Artificial Intelligence" more precisely, it is necessary to analyze the tradition of the AI models that are nowadays mentioned in connection with GenAI. Two popular and impressive examples are Stable Diffusion from Stability AI[3] and the Generative Pre-trained Transformer (GPT) from OpenAI[4]. Although their success and public reception is unprecedented, AI models attempting something similar have been around for a long time. In what follows, we present a history of GenAI and how this technology has led to the current situation. This narrative is necessarily selective and does not claim to be exhaustive.

In general it can be observed that GenAI is not tied to a specific type of AI. The current success of GenAI can be traced back to Artificial Neural Networks (NNs). However, until the rise of NNs, various other methods were used with the aim of producing similar results.

[3]stability.ai
[4]openai.com

The first attempts that can be associated with GenAI date back to the late 1960s and early 1970s. The first GenAI algorithms were all expert systems (ES). In other words, they were based on rules explicitly specified by humans. Unlike today's AI algorithms, this eliminates the need for training, which requires large data sets and appropriate learning techniques. On the other hand, ES are very limited in their capabilities. Programs designed to generate text can only generate pre-defined sentences or phrases. Drawing-ESs can only generate human-defined shapes, and ESs built for composition can only generate melodies according to predetermined rules. Between 1964 and 1966 Joseph Weizenbaum developed ELIZA, a chat program that simulated a psychotherapist (Weizenbaum 2020, 14-15). Despite its very limited conversational capabilities, users were enthusiastic about its possibilities. Although, or perhaps because, it was "only" a computer program, users entrusted it with many personal details (ibid., 19). At the same time, Harold Cohen programmed AARON, an ES for drawing images (Cohen 1995). R. Kh. Zaripov devoted himself from 1959 to a program that could generate melodies based on predefined rules (Zaripov and Russell 1969). The limitations of all three ESs are of a different nature. ELIZA can only generate answers for a limited area of knowledge and even then only on the basis of a certain set of rules (Weizenbaum 2020, 15). If ELIZA cannot provide an answer, a question is generated that more or less repeats the input (ibid., 15). For the domains of art and music, both systems had strict aesthetic rules, based on which they could compose elements (e.g., shapes and notes): "[The method] is based on the formalization and programming of certain laws of musical structure and rules of composition" (Zaripov and Russell 1969, 129). Unlike today, it is not possible for all three systems to adapt their output to descriptive inputs (so-called prompts, e.g., *compose something in the style of Mozart*).

In the years that followed, technical progress in the field of GenAI was made primarily in the area of Natural Language Processing (NLP). Expert Systems were followed by models which have the advantage over Expert Systems that they are not limited to pre-defined phrases. Instead, they can learn the statistical sequence of words (and phrases) in a language. Based on ideas from the early 20th century, Hidden Markov Models (HMM), for example, became increasingly important for these NLP tasks from the 1980s onwards, thanks to computer technology that allowed for their training (Jiang 2010, 589-590). The next great leap forward was achieved with the help of "long short-term memory" (LSTM) (Hochreiter and Schmidhuber 1997). These models were the first NNs capable of generating text of any substantial quality. Although their structure is very different, they are similar to HMMs in that they generate text autoregressively. Both share this functionality with today's popular transformer models. LSTM models were able to solve problems of earlier NNs: Because of their additional "knowledge memory", they can store information from previous words for longer and process more complex relationships. A significant advancement in natural language processing occurred in 2017 when a team of researchers developed the so-called *Transformer* architecture (Vaswani et al. 2017). The innovation introduced by Transformers is an "attention mechanism". Unlike its predecessors, HMM and LSTM models, this attention mechanism can map complex relationships within a text (between words and phrases), which is essential for successful text generation. Due to increased computing power, it is now possible to use questions as input, which are answered in real time by a transformer model (e.g. GPT).

On the image generation side, the first major breakthrough came in 2014 with Generative Adversarial Networks (GANs) (Goodfellow, Pouget-Abadie, et al. 2014). One reason for this delay in comparison to NLP is the sheer size and complexity of image data. Progress in this area has only been made possible by the computing power needed to train large NNs such as GANs. In the training process of GANs, two neural networks – the so-called generator and discriminator – are cleverly combined. The former network generates images from random noise, while the latter tries to distinguish these generated images from real training examples. Metaphorically speaking, the generator tries to outsmart the discriminator with its images. If you combine the training of both, they improve each other: the generated images become more and more similar to real images, as the discriminator also becomes better at distinguishing them. After training, the generator can now be used to generate new images from noise. A disadvantage of this type of image generation is that the generator has no incentive to be creative. The images that look most like the originals in the training dataset are the ones that are hardest to distinguish from the real thing. So there is no reason to generate something *new* (Creswell et al. 2018, 63). This problem was solved in 2022 by so-called *Diffusion Models* (e.g. Stable Diffusion) (Rombach et al. 2022). They also generate images, but work in a fundamentally different way. Unlike GANs, Diffusion Models do not attempt to generate an image from noise in a single step. Instead, they have been trained to extract (previously superimposed) noise from real images in many small steps. When given pure noise as input, the noise is reduced until an image is produced. This process can be controlled by text prompts, so that not just any image is produced, but, for example, an "astronaut on a horse" (ibid., 10687).

3.2 Conceptual Reconstruction

The second historical path we want to follow for a successful analysis of GenAI is that of the concept itself. It is by no means the case that the term GenAI has always been used in its current form – term and meaning have only grown together over the years. This historical convergence still leads to inaccuracies in meaning today. As such, it is instructive to sketch the history of the term GenAI here.

The term "Generative Artificial Intelligence" as a whole only emerged in the mid-2010s. However, similar terms were used in similar domains much earlier. This is mainly due to generative models, which can be used for classification. The idea is as old as Bayes' theorem. Generative models, in contrast to discriminative models, do not directly model the probability of a class based on the observation, but model the joint probability distribution of class and observation, from which the class can then be calculated (using Bayes' theorem) (Jebara 2004, 18-22). Accordingly, terms such as "generative models" and "generative learning" can also be found in connection with AI methods such as hidden Markov models and Bayesian networks, for example in 2001 (Ng and Jordan 2001) and 2004 (Jebara 2004). The connection between generative models and GenAI is not entirely clear. The term "generative model" explicitly describes a statistical learning method that makes no statement as to whether its output can also be used for classification, for example. However, GenAI is based on generative models and attempts to (approximately) model some ground-truth reality (its probability distribution) and not just calculate an observation-label probability distribution, as discriminative models do. This indicates that the terms are applicable to a comparable context but are not an exact match in terms of their wording or the phenomena they refer to.

To our knowledge, it was in his 2010 dissertation that van der Zant (2010, 2) used the term "Generative Artificial Intelligence" explicitly for the first time. However, he describes something that has nothing to do with the current meaning and understanding of the concept. In his work, he describes an approach with which AI can no longer only be optimized in relation to one point, but generates new goals in order to improve itself dynamically (ibid.). His understanding of the term is perhaps along the same lines as the dreams of some developers today that GenAI is a step in the direction of "Artificial General Intelligence" (AGI). We will come back to the relationship of GenAI and AGI in Chapter 5. For the time being, it suffices to note that van der Zant's idea certainly does not describe what we understand by GenAI today.

Term and phenomenon had their first real point of contact in 2014 thanks to Goodfellow and colleagues with their development of Generative adversarial nets (GANs). The term "Generative AI" does not yet exist at that time, but these generative nets describe an AI approach which is capable of generating images of noteworthy quality for the first time (Goodfellow, Pouget-Abadie, et al. 2014). This has familiarized people beyond the purely technical domain of computer science with the concept of image generation and the adjective *generative*.

A year later, the term "Generative Artificial Intelligence" reappears in a publication by Tony Veale (2015), where it is used to describe a text-generating AI approach with an application to Twitterbots. This is the earliest occurrence of the term in a context analogous to the contemporary understanding and usage of GenAI. At this moment, the reason for the lack of a precise definition of GenAI becomes evident. Indeed, Veale is not concerned with a precise definition of GenAI, nor is he interested in delineating GenAI as a field of computer science research. He employs the term "GenAI" on a single occasion, utilizing it as a catch-all designation to broadly delineate the rationale behind the intrinsic interest of his research: "As generative AI systems grow in sophistication, so do our expectations of their output" (ibid., 5). His focus is not on the field of computer science per se, but rather on the implications of machine creativity for metaphor generation.

The problem of lack of definition and precision persisted, although use was very sporadic at the time. Another example can be found in 2017 in an article on AI applications in astronomy (Castelvecchi 2017, 17). Again, the focus is not on AI, but on astronomy and how image generation methods can support it. And again, GenAI is used as a catch-all term to summarize different approaches and illustrate where they can help astronomy – regardless of their exact design.

The fact that the term "Generative AI" was introduced from outside the field rather than from within it is also indicated by the fact that it does not appear in the most influential AI papers on the subject. The paper on GANs was mentioned above. Even the seminal 2017 paper on transformers, now synonymous with successful text generation, does not mention GenAI (see Vaswani et al. 2017) once. Even in 2022, in the development paper of Stable Diffusion, one of the most successful image generation algorithms ever, only the technical basics of generative models are discussed, but the approach is not directly related to GenAI (Rombach et al. 2022).

As we have shown, there is a conceptual history to the term "Generative AI" that is not identical to its technical history. From the beginning it was used in a loose and imprecise manner to denote general functionalities regarding the generation of certain outputs and not in a strictly technical way. One might think that with the already mentioned historical convergence there is now a unique and unambiguous meaning to GenAI, but this conclusion would be premature. If we want to talk about GenAI, it is important to be aware of the technical underlying structure. But it is – depending on the exact context – possibly as important to do justice to the multiple layers and complexities that are connected to GenAI which are not satisfied by a purely technical discourse. In order to refute the idea that the term GenAI has converged to a uniform and well-defined concept, we will in the following analyse two edge cases of AI systems that hint towards a pragmatic or pluralistic understanding of GenAI.

3.3 Exemplary Reconstruction

The genesis of the term makes it clear that GenAI is not congruent with a specific technical system or model, but in its current use represents a cross-section of existing technologies. In order to demonstrate the inadequacy of a purely technical definition of GenAI, we will in the following analyze two different case studies. The analysis of the Large Language Model BERT will demonstrate that it is not as straightforward as one might think to determine whether a specific system includes or constitutes a generative model in the technical sense. The second case study of AlphaFold 2 and 3 on the other hand suggests that even in cases where the technical dimension is unambiguous, there are reasons to extend the narrow, purely technical idea of GenAI in order to accommodate the actual practice and intuition of researchers working with these systems.

Case Study 1: BERT

BERT, which stands for Bidirectional Encoder Representations from Transformers (Devlin et al. 2019), was introduced by Google in 2018 and is one of the classical machine learning models in the context of NLP. After its release it quickly surpassed traditional models such as LSTM models and constituted the state-of-the-art system for a variety of NLP related benchmarks (Rogers, Kovaleva, and Rumshisky 2020, 842). BERT is sometimes considered as an early example of GenAI, but at first glance it does not seem to include a generative component in a technical sense. While it shares some central architectural features with current LLM models such as GPT (e.g., both are transformer-based models), it is – as its name already suggests – *bidirectional*, meaning that it considers both left and right context of a given token. Unlike GPT, which predicts each token unidirectional based on the previous token, it is not autoregressive. Indeed, the vanilla BERT model was not built to *generate* text, but to excel at other NLP related tasks such as classification, understanding or translation.

Despite this fact, researchers quickly noticed that it is still possible to use BERT to generate text without changing its core architecture. This is surprising, since BERT – by design – is a so-called "encoder-only" system, which should not be able to generate text in any straightforward manner (see Footnote 4 in Devlin et al. 2019). A possible explanation for this unintentional functionality is that in order to train a bidirectional model such as BERT, the developers relied on introducing a "Masked Language Model" (MLM) during pre-training. For technical details on MLMs, we refer the interested reader to the relevant literature (see, e.g., Chapter 11 in Jurafsky and Martin 2023). The important point to be made in the context of our argument is that there is an ongoing debate in the literature if – and how – BERT (or MLMs in general) could be represented and understood as generative models in disguise (Wang and Cho 2019; Goyal, Dyer, and Berg-Kirkpatrick 2022; Torroba Hennigen and Y. Kim 2023).

Apparently, the seemingly easy task to decide if a specific system includes or constitutes a generative model is far from trivial. Against this background, it is questionable if it makes much sense to exclusively rely on a narrow and technical definition of GenAI based on generative models. It is unquestionable that the technical dimension constitutes the basis of any GenAI, but if a system has the necessary functionality to produce novel and useful outputs – to generate – it is irrelevant for most people if it includes a generative model in the technical sense. In order to emphasise this point, we will in the following consider the example of AlphaFold 2 and 3.

Case Study 2: AlphaFold

The AlphaFold project revolves around the central problem of predicting the three-dimensional structure of proteins from their amino-acid sequences. The problem of protein folding is by no means new. Since 1994 there exists a biennial competition for protein structure prediction – the Critical Assessment of Structure Prediction (CASP) –, which has been dominated by deep-learning-based approaches in recent years. While AlphaFold is not the only such approach to the prediction of tertiary structure of proteins (see, e.g., Baek et al. 2021; Callaway 2022), it is of particular interest for our purposes because of its two versions two and three: While AlphaFold 2 predicts the three-dimensional structure of proteins from their amino-acid sequences, AlphaFold 3 is "capable of predicting the joint structure of complexes including proteins, nucleic acids, small molecules, ions and modified residues" (Abramson et al. 2024, 493). On a technical level, AlphaFold 3 adds a diffusion model to the underlying structure of AlphaFold 2. This added diffusion model leads AlphaFold 3 and structurally similar systems (Lin and AlQuraishi 2023; J. Lee, J. Kim, and P. Kim 2023), as opposed to AlphaFold 2, to sometimes be labeled as GenAI (see, e.g., Erdmann, Schumann, and von Lindern 2024; Oldfield 2023; Schwaller 2023). This constitutes a prime example of what we call semi-technical discourse on GenAI: both system and model-level are addressed, but the definition of GenAI only relies on generative models. However, as we have argued in chapter 2, equating a generative model (in this case a diffusion model) with GenAI is does not do justice to the phenomenon at hand. Below, we will explicate this point with a discussion regarding the (actually relevant) functionalities of AlphaFold 2 and AlphaFold 3.

Unlike with BERT, there is no technical uncertainty about the nature of the generative model structures of AlphaFold 2 and AlphaFold 3 (AlphaFold 3 includes a generative model component, AlphaFold 2 does not). However, this does not necessarily mean their differences in technical structures would be represented in the broader discourse. For the debate among practicing researchers of biology and medicine it is mostly irrelevant if a generative model was only added in AlphaFold 3. In personal communication, researchers confirmed this intuition and stated that AlphaFold 2 already *generated novel and useful outputs* for their intents and purposes. The upgrade to AlphaFold 3 is not to be downplayed and, as mentioned above, adds additional capabilities that were not present on AlphaFold 2, but it is in the perception of practicing scientists not necessarily a paradigm shift with respect to its generative capabilities but rather an extension of the already existing generated content. The same phenomenon is observable in research papers on the use of AlphaFold 2, where the authors write that AlphaFold 2 "generates models of protein structures" (Thornton, Laskowski, and Borkakoti 2021, 1666) or that AlphaFold 2 "may have [...] success in *novel* [emphasis added] protein design" (Laurents 2022, 4). This reference to the generative capabilities of systems that lack a generative model component indicates a confusion in the debate that is independent of any technical ambiguities. In other words, the technical structure of AI systems is not a necessary condition for them to be perceived as GenAI.

Our case studies serve the purpose of conveying two important points regarding GenAI. Firstly, we have shown with the example of BERT that the technical configuration of GenAI, despite its crucial role as a basis for GenAI models and systems, is itself part of an ongoing debate in the technical literature. As such, relying on a purely technical definition of GenAI based on generative models – as is common practice in the semi-technical discourse – is not unambiguous and can be problematic. Secondly, based on our discussion of AlphaFold 2 and AlphaFold 3, we argued that even if there is a clear-cut difference in generative modeling capabilities, this is not necessarily reflected in the relevant functionalities and the associated discourse. Our case study made this explicit by revealing a tension between the narrow, semi-technical definition of GenAI based on generative models and the actual attribution of generative capabilities regardless of the technical basis. The following chapter aims to elucidate the aforementioned confusion by presenting a number of functionally relevant aspects which can help to structure and clarify the public discourse on GenAI.

4 Aspects of GenAI

As we have shown in the previous chapters, the technical, semi-technical and public discourses about GenAI are not isomorphic. Rather, the public dimension transcends the technical one in certain important aspects. It is our goal in this chapter to analyse this incongruity and to propose a set of four aspects – *(multi-)modality*, *interaction*, *flexibility* and *productivity* – that help to structure this debate by picking out relevant functional characteristics of GenAI that cannot be settled within a purely technical discourse. This is necessary because, as we showed above, the narrow, semi-technical definition of GenAI based solely on generative models is unsatisfactory. As such, these aspects can be understood as a first step towards *defining* GenAI beyond its technical basis.

Importantly, we do not claim that this list is exhaustive or that the four aspects are mutually exclusive. Rather, we propose these different dimensions in order to span the public discussion landscape on GenAI and help to allocate oneself in this abstract space.

4.1 (Multi-)Modality

The modalities of GenAI significantly determine the debates about it. Looking at the public discourse, three modalities are commonly associated with GenAI: text (language or code), image (or video) and sound (music or speech). In addition, authors usually provide little technical information, preferring to mention a few well-known exemplary models such as GPT or DALL-E (see, e.g., Singleton 2024; Coursera 2024; Eliassi-Rad 2024; Satariano 2024).

Discussions about modalities did not arise with GenAI, but have always been important in the technical debate, as different modalities require different technical approaches. Various fields of AI research are solely focused on a single modality. For example, Natural Language Processing (NLP) deals with language (text and speech) while Computer Vision is obviously pointed at image and video data. However, in the public discourse surrounding GenAI these rather technical distinctions are mostly irrelevant. Instead, the debate is mainly shaped by the capabilities of GenAI to deal and interact with humanly accessible modalities, e.g., receiving natural language prompts and producing relevant images based in this input. An AI performing well on tasks for these kinds of modalities can be perceived as intelligent or even threatening to humans. On the other hand, AI models that deal with multiple modalities, but are used for "non-human" tasks such as data analysis, are usually not seen as a threat or competition to humans in the public discourse. Instead, they are perceived as capable tools, not as intelligent machines. This distinction suggests that modalities are an important factor for the perception of AI systems as GenAI – but only if they include humanly accessible modalities such as natural language, images or sounds.

To further illustrate this point, think back to our case study of AlphaFold above. We showed that there is a relatively clear technical distinction between the non-generative AlphaFold 2 and the generative AlphaFold 3.

However, for all intents and purposes of the practicing scientist, AlphaFold 2 *generates* new data – in this case, the 3D structure of proteins. In the public debate, on the other hand, neither AlphaFold 2 nor AlphaFold 3 are considered GenAI. We argue that one reason for this fact is precisely because of the modalities of both AlphaFold versions: They do not generate text, images or sound and are therefore regarded by the layperson as little more than powerful tools. The same applies to other examples such as DeepBlue[5] and AlphaGo[6]. Both generate new data, but it is not text, image or sound data, but new game moves. The modalities that an AI system can process are obviously important in assessing whether a system is deemed GenAI in the public discourse – in contrast to the exact details of its technical functionality. Looking at the history (see chapter 3), it is clear that text, image or sound output is not *necessarily* connected to GenAI, as there were AI models that produced results similar to GPT or DALL-E long before the concept of GenAI, such as ELIZA (Weizenbaum 2020), AARON (Cohen 1995), or compositions by Zaripov (Zaripov and Russell 1969). While modalities were always an important factor in discussions of AI, GenAI distinguishes itself by the central importance of processing *multiple* modalities.

Today, output (whether speech, code, music, voices, images or video) can be influenced and modified at will by text prompts. Even AIs that were originally limited to text, such as the GPT series, can process visual input with the GPT4 version (OpenAI 2023). Does this mean that the only difference between previous AI models and today's GenAI is *multi*-modality? The answer is no. The boundaries of multi-modality are fluid and quickly become blurred when moving away from large language or image models. The Visual Question Answering (VQA) tool by Malinowski and Fritz is a good example. The user can ask (via text promts) for the position of objects in a scene and gets a text based answer. Although VQA fulfils all the above conditions (images and text questions as input and text answers as output (Malinowski and Fritz 2014)), it would hardly be classified as GenAI. The reason is that its input and output is very rudimentary and based on predefined categories (ibid., 8). Thus, the classification as GenAI seems to not only be based on modalities of an AI. It is also the flexibility within and interaction with these modalities that is important for an AI model to be labeled as GenAI. While *multi-modality* is not a new invention and present in previous AI applications, it is central to the public interest in GenAI. By combining humanly accessible modalities, multi-modality is an important step towards a seamless integration of AI systems in our life and constitutes the foundation of other important aspects of GenAI, like *interaction* and *productivity*.

4.2 Interaction

An important feature that distinguishes GenAI from other types of AI is its intuitive interaction capabilities. Today, the AI systems that fall under the term GenAI are particularly accessible to laypeople. Other types of AI are not excluded from intuitive interaction, but models that deal with humanly recognisable text, images and sound are predestined to be integrated into easily accessible systems.

The clearest example of this phenomenon are language models (see e.g. OpenAI 2023; Narang and Chowdhery 2024). There are two processes at work. First, language models are tasked with generating human-readable text as output (either in conversation, or as translations, etc.). Second, while they are not inherently capable of handling human-readable input, the better they can handle diverse, complex input, the more likely they are to be adopted. This interaction process is supercharged if the AI's input and output are (partly) of the same modality, and the output of one generation cycle can be used as input for the next.

This principle can also be seen in GenAI models that deal with sound (see, e.g., Radford et al. 2023). Any model that works with speech input/output must, by definition, be able to work with human language. The ease of interaction for the layperson is least obligatory for image generation tools (see, e.g., Rombach et al. 2022). The connection between textual input and visual output is not as direct as for language models. However, the second process of language models also applies to image generation: the easier it is to use, the more users there will be. An image generation tool that requires a tabular description of which parts of an image should be filled with which objects loses its appeal and even its usefulness.

In addition to the ease of interaction described above, there exists another important factor about GenAI that reinforces its interaction capabilities: models typically considered as GenAI are applicable to their own output. It is possible to use their output as input for the next generation cycle. This is necessary for the conversational capabilities of text generation models, but image generators are also capable of adapting their generated images based on new prompts. This iterative self-application is a cornerstone of GenAI models based in the modalities it uses and massively influences their interaction capabilities.

The above examples show an important circle that leads to easily accessible GenAI. First, as mentioned in the previous chapter, the modalities of AI models that are called GenAI are humanly understandable modalities. Secondly, this makes it easy for laypeople to interact with them. Thirdly, easy interaction contributes massively to their popularity. Finally, this popularity forces developers to support ever better interaction capabilities. For example, by broadening the scope of the model and building so-called "Foundation models" (see next chapter 4.3)

[5] ibm.com/history/deep-blue
[6] deepmind.google/technologies/alphago

that can work on a variety of tasks (Bommasani et al. 2021, 3). This in turn increases the humanly accessible modalities (see step one) and their usefulness for everyday problems. While interaction with AI systems is not specific to GenAI, we argue that it is an important and central aspect of it.

4.3 Flexibility

One can observe an explosion in AI coverage – especially in relation to GenAI – in the public domain (see, e.g., Singleton 2024; Coursera 2024; Eliassi-Rad 2024; Satariano 2024). As we have seen in the historical overview, technological developments, while accelerating, are a gradual process. Technical progress brings new possibilities, but neither the ideas nor the application are particularly new. What has changed massively is the scope of the currently developed systems, which introduces an unprecedented *flexibility* for the users. New text-generating GenAI models are known as "Foundation Models", which are capable of simulating conversations on any conceivable topic. GPT and similar models can simulate the writing style of any author and are, at the same time, able to traverse complex math problems, play games, etc.

While interaction plays a crucial role in the accessibility of GenAI, earlier models such as ELIZA (Weizenbaum 2020) were also able to simulate conversation in English. However, earlier models were much more limited in their knowledge. ELIZA had to be *retrained* (given a new set of rules) for conversations other than as a therapist. A similar trend can be seen with image-generating models. Although the first models in this area appeared much later, their limitations were not as pronounced as for text generation. Today, however, their flexibility is often even greater. Open source applications such as Stable Diffusion can be fine-tuned to generate images in niche art styles or in the styles of specific artists. This ties into our expectation of creativity with regard to these models. Today, they are capable of producing an unimaginable number of unique images and are no longer limited to generating photorealistic human portraits, as StyleGAN was a few years ago (Karras, Laine, and Aila 2018).

This change is partly due to the increase in computing power that made these extensions possible. In large part, however, this new flexibility was a conscious design decision by the developers and led, among other things, to the creation of GPT: a Generative *Pretrained* Transformer.

4.4 Productivity

There is one fact about GenAI that is not directly related to the models or their inputs and outputs, but to the way people use these new systems for professional and personal tasks: productivity. The public debate is already predicting large productivity gains from the use of GenAI (Brynjolfsson, Li, and Raymond 2023; Chui et al. 2023). This is not to say that GenAI systems are the only ones capable of improving productivity. On the contrary, specialised AI models have been able to do this for years in their respective domains: predictive maintenance, spam filters, automated investments. In itself, GenAI is no more *productive* than other types of AI. There is no *a priori* difference in the way it produces its outputs or processes its inputs that would make it more productive than other AI models.

What makes GenAI a superior candidate for productivity improvement is a combination of the aspects we have introduced above, as they allow people to use GenAI systems in a variety of settings and to apply them to a variety of problems. Ease of interaction, (multi-)modality and flexibility support the foundational nature of the models and ensure their application in a diverse range of different contexts. As such, GenAI may be able to generate productivity gains (with varying intensity) in a variety of sectors (Brynjolfsson, Li, and Raymond 2023). Thanks to this wide applicability, it is easy to imagine that GenAI systems will lead to productivity gains in almost every field of work "from banking to life sciences" (Chui et al. 2023), which might explain why productivity seems like a natural candidate to include in our set of relevant aspects. Notably, gains in productivity are not restricted to economic metrics, but include enhanced creative output or other, non-work related tasks. For example, artists already start to use GenAI models in their work and generate new workflows and never before seen products (for a discussion of possible GenAI use-cases, see Vigliensoni, Perry, and Fiebrink 2022).

It is interesting to observe that widespread productivity in turn requires greater flexibility and interactive capabilities of GenAI, which links it back to the other aspects we have introduced. In this sense, these four dimensions influence and enhance each other, which further substantiates our claim that they pick out some relevant structural characteristics in the current GenAI discussion landscape.

5 Conclusion

In the previous chapters we have tried to work out central distinctions and differentiations with regard to the concept of GenAI, both historically and systematically. We have identified various, sometimes contradictory, sources and contexts that are repeatedly used in the field and which potentially explain the prevailing *confusion about Diffusion* (and other GenAI models). We showed that there is not a single, unambiguous concept for understanding GenAI: It is not possible to find an exhaustive list of necessary and sufficient conditions for characterizing

GenAI, as there are always counterexamples that elude a uniform characterization. A purely technical definition does not do justice to the multiple layers and complexities of the public discourse. This does not mean, however, that there is nothing to be said about this discourse and its different aspects. We identified four main features in order to structure the discussion landscape – *(multi-)modality*, *interaction*, *productivity* and *flexibility* –, which can be used to distinguish GenAI from other forms of AI and thus represents a first step towards *defining* GenAI.

These aspects potentially function as an explanation to the question of why GenAI is so fascinating and to the associated hype in the public domain. GenAI opens up a total field of possibilities that can be utilized both in a private as well as an economic context. As Foster pointed out, due to its generative capabilities, GenAI is not deterministic but randomly open for "individual samples generated by the model" (Foster 2019, 3). Because it is not only focused on one function but contains an unprecedented freedom to use it in different contexts, it approaches a status that seems qualitatively different from more traditional AI applications and hints for the first time towards an Artificial General Intelligence. Even though the concept of AGI and associated predictions of future technological development are sometimes considered as problematic or unscientific (Altmeyer et al. 2024; Fjelland 2020), it is undeniable that (1) the prospect of such systems sparks substantial public interest and that (2) current GenAI is the closest candidate for such systems.

In this field of (multi-)modality and multi-functionality, there is a variety of different applications that opens up the realm of productivity and creativity in an unprecedented manner for a large share of people around the globe. It combines a dynamic, user-oriented process with the effective creation of a useful and new product (Zhou and D. Lee 2024). Importantly, this framing of a convergence of GenAI towards a state of AGI is far from fictional scenarios about dystopian nightmares of AI taking over control – or a utopia where AI solves all of humanities problems for that matter. Instead, it tries to focus the debate on the actual functionalities and potential risks of current GenAI systems and the way they already influence our private and working life.

The four aspects we have worked out can be described as a form of "collaborative creativity" (Kaufman and Sternberg 2019, Part IV) between humans and AI systems. In this realm of possibilities and potentiality, GenAI is a unique and novel mode of operation and clearly detached from earlier reductionist misunderstandings regarding machine creativity (Schmidhuber 2010). It is not just tailored to a specific process, but rather to a multi-functional range of applications which redefines the interface between humans and AI. It shapes a new intersection between the real and the digital world, a paradigm shift that has already arrived in the public discourse: "While each of these architectures – GANs, autoregressive networks, and diffusion models – sits on a bedrock of mathematical rigor, their real-world applicability extends far beyond sterile equations." (Corbeel 2023)

The aspects of *(multi-)modality*, *interaction*, *productivity* and *flexibility* we have proposed in this article are attempts to map out exactly this interface. As such, they help to clarify what function and relevance GenAI has beyond its technical basis.

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