Exploring Generative Artificial Intelligence: A Taxonomy and Types

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Abstract

Generative Artificial Intelligence (GAI) is a prevalent topic in recent research and business, seemingly taking the position of a disruptive technology that has the potential to significantly transform industries ranging from productivity (e.g., ChatGPT-4) to creativity (e.g., DALL-E). While the emerging scientific discussion on GAI covers a variety of fields and issues, such as privacy, accuracy, and application scenarios, this paper sheds light on the business side of GAI by investigating the morphologic nature of start-ups and incumbents leveraging GAI. Based on the structured analysis of 100 real-world instances, we report on a taxonomy of GAI applications and services that advances our practical understanding, strengthens the distinguishability, as well as adds clarity to the discourse of GAI potentials. We provide an initial framework and five types of GAI, namely Generator, Reimaginator, Synthesizer, Assistant, and Enabler, that are informed by the core characteristics of the technology paradigm.

Keywords: Generative Artificial Intelligence, Machine Learning, LLM, Taxonomy, Typology

1. Introduction

Artificial intelligence (AI) has profoundly transformed how individuals, companies, and ecosystems live, work, and operate for the last decade. Through novel data analyses and (human) sensemaking, AI has facilitated unprecedented efficiencies as well as conveniences, disrupting industries and even everyday life (Ågerfalk, 2020; Berente et al., 2021; Fügener et al., 2021). This transformation initially took root in the form of discriminative AI, which focuses on classification and prediction. Recently, the technological horizon has evolved into a new form of AI, namely *Generative AI (GAI)*, capable of automatically creating new data and content that is nearly indistinguishable from human output (Mondal et al., 2023). Recent applications, such as ChatGPT (OpenAI, 2023), DALL-E (Ramesh et al., 2022), and Midjourney gain growing attention and deliver impressive results that manifest in realistic outputs fulfilling the user's requests (Hu, 2023; Teubner et al., 2023). The shift towards generative AI might mark a turning point in the acceptance and adoption of AI because of the capabilities to synthetically generate diverse media content, including images, text, and audio, which is potentially fueling a new era of AI-driven efficiency but also innovation and creativity (Susarla et al., 2023; Teubner et al., 2023). However, given the ever-changing and rapidly evolving landscape of generative AI applications, there is an urgent need for a comprehensive conceptualization of the capabilities and characteristics of these applications to structure and capture their potential.

While the academic community is in the process of examining the broader and general attributes and implications of AI, studies of generative AI and its subsequent applications are still emerging and tend to take a more conceptual and/or theoretical perspective. Previous studies, for instance, have primarily focused on the transformative impact of generative AI on areas such as education (Cooper, 2023; Lund et al., 2023), work (Brynjolfsson et al., 2023; Noy & Zhang, 2023), and even tasks that were once considered beyond the scope of automation, including creative work (Haase & Hanel, 2023; Stevenson et al., 2022). A systematic examination of real-world instances is yet to be conducted, leaving key aspects of the properties and characteristics largely undefined. This ambiguity is problematic, as a lack of understanding hinders the ability to conceptualize generative AI within theoretical and practical frameworks. Moreover, from a practice viewpoint, it hinders making informed

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decisions (e.g., investments) concerning appropriate GAI applications that support a certain task. To advance this promising field, we pose the following research question (***RQ***):

What are the dimensions and characteristics of generative AI?

To address our research question, we followed a two-staged research design: In the first step, we employed Kundisch et al. (2022) and developed a comprehensive taxonomy of generative AI that is grounded in an empirical investigation of 100 real-world applications to capture the main attributes of this particular phenomenon. In a follow-up step, we applied our taxonomy as well as performed a combination of cluster analysis and qualitative case analysis to deduce a set of five common GAI types.

With that, we make a threefold contribution: **First**, we provide an empirically grounded taxonomy of generative AI that outlines the key dimensions and characteristics allowing us to describe, differentiate, and hypothesize about this phenomenon. **Second**, by classifying 100 distinct applications with our taxonomy, we identify prevalent types of generative AI that emerge from practice. They provide a more abstract understanding of how this novel technology is implemented in real-world instances, as well as aid in positioning and selecting tools from a certain class of purposes. **Lastly**, by bridging theoretical conceptualization and practical implementation through our conceptual framework, we offer valuable insights for future research, potentially guiding the development and evaluation of generative AI.

The remainder of this paper is structured as follows: We outline the theoretical background of generative AI with its concept and algorithmic processes. Afterward, we describe the research design with its subsequent activities to design our resulting artifact. Then, we present our taxonomy and a set of GAI types. Finally, we demonstrate our findings, discuss the results, and draw implications for theory and practice before concluding with conclusions, limitations, and a research outlook.

2. Generative Artificial Intelligence

The concept of AI is not inherently new; as early as 1950 (McCarthy et al., 2006), fundamental paradigms were created for the development of machines capable of mimicking human abilities such as sensing, reasoning, and thinking (Berente et al., 2021; Wang et al., 2019). After more than half a century of technological development and the associated advances in algorithmic and computational performance, as well as the availability of large datasets, AI now occupies a significant role in almost all aspects of life (Berente et al., 2021; Brynjolfsson & Mitchell, 2017; Taddeo & Floridi, 2018).

In general, GAI, similar to the term AI, is an umbrella term for a class of algorithmic approaches (Figure 1). The foundational technology underlying the capabilities of recent GAI systems is based on *deep generative models* (DGM) that generate new datasets and content from existing data utilizing deep learning (DL) approaches (Gm et al., 2020; Tomczak, 2022). DGMs differ from discriminative models in the *objective* (generation of data vs. determination of decision boundaries) and the underlying *algorithmic execution* (Tomczak, 2022; Weisz et al., 2023). Generative models understand the underlying structure of the data and the process that generates it, in contrast to discriminative models, which concentrate on explicitly modeling the relation between input attributes and output labels (Jebara, 2004). Non-DL-based generative models such as Hidden Markov Models play a minor role in recent discussions on GAI and realistic data generation (Gm et al., 2020; Hacker et al., 2023). Hence, we will focus on GAI based on DGMs in the following.

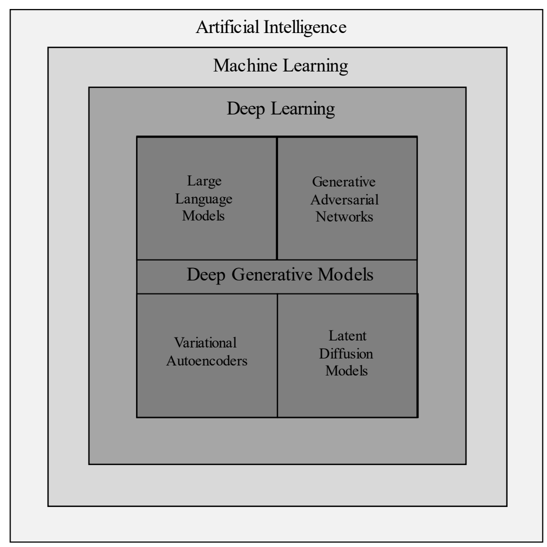

Figure 1. Positioning the Concepts of GAI

There are four ways to classify DGMs, namely:

(1) Generative Adversarial Networks (GAN) (Goodfellow et al., 2020) consist of two competing neural networks: a generator creating realistic data samples and a discriminator distinguishing between real as well as generated samples (Pan et al., 2019). Both networks are trained in tandem, resulting in an adversarial competition in which the data generation capability optimizes over time (Janiesch et al., 2021). Core application areas of GANs are image generation and processing, object recognition and segmentation, as well as natural language processing (Aggarwal et al., 2021; Gui et al., 2023).

(2) Variational Autoencoders (VAE) use neural networks to learn encoding compressed input data into a lower-dimensional latent space and decode the data by reconstructing the original data from the latent space representation (Kingma & Welling, 2014). By optimizing a variational lower bound on the data likelihood in a probabilistic approach, VAEs can generate new samples that resemble the original data distribution. Typical use cases for VAEs are generating synthetic data, image reconstruction, and anomaly detection (Wei & Mahmood, 2021).

(3) Transformer Architecture has become the state-of-the-art approach for natural language processing models. Transformers are a particular kind of neural network architecture that use self-attention processes to capture long-range dependencies in the input, which makes them suitable for complex language modeling problems (Vaswani et al., 2017). The main field of application for transformers is the processing of languages, where they are used similarly to generative-pre-trained transformers in combination with large language models (Brown et al., 2020).

(4) Latent Diffusion Models (LDMs) are grounded in the concepts of denoising score matching and contrastive divergence for stochastic data generation (Rombach et al., 2022). Starting points here are simple initial distributions (e.g., Gaussian noise), which are used stepwise for noise reduction in a predefined diffusion process through a latent space as part of the generation process (Ho et al., 2020). LDMs are well-suited for tasks that require high-quality and precise outputs, such as high-resolution image synthesis (Takagi & Nishimoto, 2023) or 3D shape generation (Zeng et al., 2022).

Regardless of the algorithmic underpinnings, the primary goal of GAI is the generation of new, probabilistic data with different outcomes based on the same input, which is what primarily distinguishes this type of AI from discriminative AI.

3. Research Design

Taxonomies are among the well-established classification systems in IS that help conceptualize both existing and novel phenomena. They describe objects of interest by formalizing their key characteristics (i.e., attributes of an object) (Glass & Vessey, 1995; Schoormann et al., 2022). Given the speed of socio-technical progress and technological advancements, such as those faced in our research stream of AI, taxonomies assist research and practice in their efforts to understand new developments and changes (Kundisch et al., 2022). They provide a snapshot of the current situation and enable us to explore and hypothesize about it. Because of their ability to do so, prior literature has proposed taxonomies for technologies that relate to our context, including AI literacy (Heyder & Posegga, 2021), AI service platforms (Geske et al., 2021), and AI for cybersecurity (Gerlach et al., 2022).

To achieve our goal, we adapted the method from Kundisch et al. (2022) which follows the basic principles of design science research and thus allows for rigorous designing an artifact, here in the form of a taxonomy. The method consists of detailed steps from specifying the observed phenomenon, across building and evaluating the taxonomy, to purposefully presenting the results. In the following, we outline how we adapted these steps by reporting on four main clusters of activities: (1) problem and solution objectives, (2) design and development, (3) demonstration and evaluation, and (4) communication.

3.1 Problem and Solution Objectives

GAI is a rapidly evolving phenomenon and has received significant attention in recent years through new technological developments, such as ChatGPT (OpenAI, 2023) (*phenomenon*). In addition to the knowledge available in existing research (e.g., Dwivedi et al., 2023; Susarla et al., 2023), we sought to add insights from empirical investigations and craft a set of preliminary types of GAI applications (*purpose*). With their ability to capture both conceptual and empirical data collected from real-world objects, a taxonomic approach seems suitable for pursuing this paper's goal of understanding GAI. An overview of the key features of GAI applications (*meta-characteristic*) is helpful for researchers interested in investigating this class of artifacts that spread across all areas of life, as well as for practitioners to orient themselves to what is actually out there (*target group*).

3.2 Design and Development

During the taxonomy design, researchers can select between two distinct approaches (Nickerson et al., 2013), namely 'conceptual-to-empirical' in which the characteristics and dimensions are derived from theory, and 'empirical-to-conceptual' in which real-world objects are examined. In this paper, due to the aforementioned focus on empirical insights, we performed two empirical-to-conceptual iterations by analyzing a series of existing GAI applications.

First, we constructed a database of 100 empirical objects representing a GAI application. For this, we explored the web to find diverse sources from which we picked samples randomly (Yin & Campbell, 2018). These included well-established sources, such as *Dealroom* or *Github*, but also social media posts that, due to the actuality and impact of GAI, comprises posts reporting “the newest GAI apps.” For example, we searched *LinkedIn* and the associated profile “Generative AI” and *Twitter* posts (Generative AI, n.d.; Huang, 2022).

Second, building on that, we organized the sample of 100 empirical objects into smaller sub-samples to make them more manageable. Therefore, the first 30 GAI applications were used to construct the first version of the taxonomy (1st iteration) and, most importantly, to get an orientation for the broader field of investigation. We extended the initial taxonomy (from seven to twelve dimensions) and used it as a frame of reference to analyze the next sub-sample of 40 empirical objects (2nd iteration).

Third, we used the taxonomy to recode the complete sample of 100 GAI applications and managed to classify all objects in ten dimensions (3rd iteration). After reaching saturation, we inductively abstracted from all characteristics to group them under meta-dimensions (Nickerson et al., 2013). Resulting, we argue that the robustness is given of the taxonomy (i.e., no dimensions and characteristics were significantly altered in the final iteration).

3.3 Demonstration and Evaluation

To ensure that our designed taxonomy is valid, we checked the ending conditions that specify when to stop with the iterative process (Kundisch et al., 2022). Since we were able to meet all specified objective and subjective ending conditions, we decided to finalize the taxonomy (*ending conditions*).

Moreover, for investigating the applicability of the taxonomy (*evaluation*), we followed Szopinski et al. (2019) and employed the taxonomy to classify our set of 100 GAI applications. This allows us to demonstrate the taxonomy as well as theorize about common relationships between the characteristics and dimensions derived (see Section 5).

3.4 Communication

For visualization, we draw on a morphological box that is a widely accepted style in IS research and beyond (*report*). Because this style is used in both practical and academic contexts, we are confident that the taxonomy will be best understood and used by our target groups. Besides, we abstracted common configurations of the taxonomy’s characteristics in order to propose a series of GAI types that provide additional orientation for users.

4. A Taxonomy of Generative Artificial Intelligence

In this section, we present the taxonomy for generative AI that covers three meta-dimensions, ten dimensions, and 38 related characteristics (see Figure 2). These characteristics are either mutually exclusive (ME) or non-exclusive (N); we decided to use some Ns in order to increase the readability. The numbers in brackets refer to the GAI applications classified by means of a certain characteristic. As some of the dimensions are not mutually exclusive, the numbers in one dimension may exceed 100.

	Dimension	Characteristics						Mutual
System Design	Input	Text (79)	Image (22)	Video (10)	Sound (5)			N
System Design	Modality	One-to-One (57)	One-To-Many (29)	Many-to-One (10)	Many-to-Many (4)			ME
System Design	Output	Text (53)	Image (40)	Video (16)	3D-Model (9)	Sound (6)		N
System Design	Operation	On Premise (17)	Managed (87)					N
System Access	Interface	Web (64)	Mobile (10)	Desktop (16)	Integrated (23)	API (17)		N
System Access	Openness	Open (3)	Semi-Open (17)	Closed (80)				ME
System Access	Fine-Tuning	Prompt (28)	Data (35)	None (35)				N
System Access	Extension	Plug-In (17)	Domain-Specific (9)	None (69)				N
System Value	Value Proposition	Generation (67)	Reimagination (28)	Assistant (30)				N
System Value	Revenue	Free (18)	Freemium (19)	Subscription (44)	Credit (15)	One-Time (2)	Model (2)	ME

Figure 2. Characterizing Generative Artificial Intelligence

4.1 System Design

Generative AI applications provide the user with a wide range of different input capabilities and result artifacts. System design tackles these options and the combinatorial possibilities associated with them.

Input specifies what type of data is provided by the user and processed by the generative AI. The most prevalent input types are *text*, *image*, *video*, or *sound*. Code is a domain-specific version of *text* which still adheres similarities with processing natural languages. Thus, the underlying foundation models do not significantly differ compared to natural language (Feng et al., 2020). A GAI application may allow users to input multiple input types, for example, an image with a supplemental textual prompt (Liu, 2023). So, this dimension is *not mutually exclusive*.

Modality refers to the versatility and flexibility of generative AI in terms of input and output capabilities as well as examines how many data types can handled simultaneously. *One-to-one* applications accept a single type of input and generate a single type of output, for instance, a text-to-text application like a chatbot. *One-to-many* applications generate multiple outputs, such as textual descriptions and images, based on a single input. Contrarily, *many-to-one* and *many-to-many* modal applications handle numerous inputs meaningfully to generate respective outputs. Thus, this dimension is *mutually exclusive*.

Output concerns the type of data created by generative AI. *Text*, *image*, *video*, *3D-model*, and *sound* are the central output characteristics. The diversity in output illustrates the wide range of possibilities offered by generative AI. Various GAI applications offer editing capabilities, for example, improving or altering images. Nevertheless, new outputs types can also be generated, such as 3D-models based on text or image prompts (Gao et al., 2022; Poole et al., 2023). Based on the multi-modal outputs possible, this dimension is *not mutually exclusive*.

Operation describes the mode of deploying and managing generative AI. Depending on the use case and requirements for employing a generative AI application, the application can either be *managed* by a (platform) provider or self-hosted *on premise*. Especially for critical business use cases dealing with sensitive data, some GAI applications allow to self-host on premise, ensuring data protection and sovereignty. As on premise is usually offered as an optional extra for enterprises, this dimension is, therefore, *not mutually exclusive*.

4.2 System Access

Customization and accessibility of AI applications plays a central role in their adoption (Pillai & Sivathanu, 2020). System Access aggregates these possibilities for generative AI applications from both a technical and a content perspective.

Interface distinguishes the mediums through which users interact with GAI applications. The identified interface characteristics comprise *web, mobile, desktop, integrated,* and *application programming interface (API)*. Generative AI designers opt for various interface options to serve different user needs and contexts. For instance, *web-based interfaces* offer broad accessibility without needing to install specific software. *Integrated* interfaces refer to applications operating within other software, such as Midjourney instantiated as a Discord bot (Midjourney, n.d.) or image generators in Photoshop and Blender. This dimension is *not mutually exclusive* because applications can be served through multiple interfaces.

Openness specifies the degree of transparency offered by the providers of generative AI applications regarding the technological details, e.g., architecture or models employed. Primarily, we differentiate between *open* (i.e., complete information such as open-sourced code and documentations), *semi-open* (i.e., partial information such as about the AI model provider), and *closed* (i.e., proprietary without any information) applications. This dimension is *mutually exclusive*.

Fine-Tuning addresses the options to customize the output of generative AI applications. This aspect allows users to influence the generated results to their liking, resulting in a premier form of personalization. *Prompt* based fine-tuning, i.e., the use of specific input directives, guides the AI's generation process. On the other hand, *data* fine-tuning involves training the AI model on a specific dataset to tailor its outputs. This could encompass the provision of a domain-specific text corpus or a set of reference images. A combination of both fine-tuning techniques is possible, making this dimension *not mutually exclusive*.

Extension characterizes how generative AI applications can expand their capabilities beyond the initial features provided by the underlying model. One approach to enhance the functionality is by implementing options for *plug-ins*. For instance, ChatGPT offers *plug-ins* to incorporate external services such as Expedia for connections to travel platforms. Another option is to provide *domain-specific,* pre-fine-tuned models for the user to choose from. Examples include financial text generators or specialized comic or anime image generators. This dimension is *not mutually exclusive.*

4.3 System Value

The development of GAI is extremely cost-intensive. System Value addresses both the value proposition for the end user and for the provider from a holistic perspective.

Value Proposition refers to the primary benefit or utility that generative AI applications offer to the users. Despite the high variance of different applications, four characteristics can be derived. The first is *generation*, which propose value through, generation of new content from the ground up to save time and resources (Mondal et al., 2023). *Reimagination* involves the transformation of existing data into novel ways. For instance, different styles can be applied to images or a 2D images is converted into a 3D model (Gao et al., 2022; Kwon & Ye, 2022). Finally, *assistants* refer to applications that support users in performing tasks by generating useful responses, suggestions, or actions (Brynjolfsson et al., 2023). As generative AI applications might advertise multiple values, this dimension is *not mutually exclusive.*

Revenue corresponds to the various business models and pricing structures implemented by generative AI applications. This dimension outlines the financial investment required and the type of access granted in return. There are a variety of pricing models implemented by application providers that are also adopted across other IS artifacts (Lehmann & Buxmann, 2009). These include *subscriptions* based on regular fixed rates, *one-time* payments for a license purchase, and no payments for a *free* usage. Moreover, *freemium*-based revenue models offer basic features for free, with premium features (e.g., enhanced capabilities or faster computation) available for a fee. *Model* pricing allows users to pay for certain pre-trained models, such as highly optimized or less complex ones. The *credit-based* characteristic refers to applications where users purchase credits to access specific features or services. These variable rates are based on the actual usage, allowing users to pay only for the features or services they need and have used. For example, text generation applications might bill users per processed tokens (i.e., common sequences of text characters). Since the revenue models are not combined in most of the cases is, this dimension *mutually exclusive*.

5. Towards General Types of Generative Artificial Intelligence

To gain further insight into the characteristics of GAI applications and to provide a classification scheme not only for individual applications but for the entire artifact class, we theorized about more general types of GAI. To do so, we combined an agglomerative hierarchical clustering algorithm with a qualitative case analysis in a two-step approach based on our final taxonomy. As the first step, we classified 100 GAI applications using our taxonomy (i.e., demonstration) and clustered them using Ward's method as well as the Euclidean distance metric in a hierarchical cluster analysis (Jain et al., 1999). This form of analysis is particularly useful to differentiate groups of objects based on the similarity of their characteristics (Punj & Stewart, 1983), which completes our previous taxonomy research. As a second step, guided by the initial clustering, we qualitatively analyzed the underlying data based on the taxonomy's dimensions. We added the qualitative analysis to our procedure as the quantitative results alone did not provide powerful descriptions. Informed by the insights, we conducted several author meetings in which we abductively derived five GAI types by elaborating on their explanatory power.

Following this, we next outline the five distinct types of GAI application.

Generators (Type I) offer capabilities to create novel and innovative content based on only few user inputs (e.g., text-to-image generators). The novelty of outputs is mainly influenced by the underlying, pre-trained generative models and the user's prompt (Oppenlaender, 2022). Hence, the *degree of modification* is focused around *creating* new artifacts and aims for *innovation* with its recombination of the pretrained model guided by the user's input (e.g., text-to-image generators like Midjourney or text-to-video generators like Synthesia).

Reimaginators (Type II) pursue the goal of reinterpreting data in a novel way. The input serves as the basis for editing while the semantics behind the content remain rather stable. From a creativity perspective, reimaginators *innovate* existing data material such as images, while only *modifying* parts of the input's contextual semantics. For instance, image-to-image reimaginators keep the original subjects of photos and only change the style, expand the images beyond their margins, or alter objects with new variations (e.g., runwayML).

Synthesizers (Type III) are applications which provide the capability to generate entirely synthetic data for use cases such as the training of AI models or the establishment of large IT test landscapes. Creating specialized and pre-labeled synthetic data allows AI-developers to train more diverse models by mitigating data bias or enables researchers to work with realistic data without violating data privacy policies. The required level of creativity is rather low, since the resulting synthetic output is strongly based on the original input. However, the objective is still the creation of something new, a synthetic modification of the original artifact (e.g., Syntho and Synthesis AI).

Assistants (Type IV) support the user within an application domain (e.g., software development, law, accounting) with domain-specific specialized knowledge or capabilities. For this purpose, the applications were trained with domain-specific artifacts (e.g., source code, legal documents, etc.). Hence, low *degree of creativity* and *modification* underline the inherent features of assistants for improving and doing things better while *preserving* the user's data with minimal modifications. Typical examples for that type of GAI are programming assistants (e.g., GitHub CoPilot) or legal assistants *(*e.g., CoCounsel*)* that require sophisticated user input data (e.g., source code, documents) to conduct marginal refinements and improvements to match the user's needs.

Enabler (Type V) offer the necessary infrastructure for supporting processes like training, fine-tuning, or hosting generative AI applications. While typical infrastructure service providers, such as Amazon Web Services or Hugging Face, provide raw computing power as well as model hosting, generative AI enablers aim to make applications easy to use without any technical prior knowledge. Applications such as Graviti, or Stable Diffusion Reimagine simply host GAI models developed by third parties. Moreover, enablers like TrainEngine.AI and Dreamlook.ai offer training capabilities that allow users to easily fine-tune their models with their own data. Lastly, enablers offer enterprises holistic platforms with various generative AI tools that can be integrated into their information systems (e.g., Writer and Cohere). Enablers are a cross section of all types without distinct boundaries toward their *degree of creativity* and *modification*.

Drawing from the types and the discussions, we identified two core aspects for generative AI (see Figure 3): **Creativity** as the degree of transformation within the generation process (Nagasundaram & Bostrom, 1994), which distinguishes between *innovate* (i.e., aiming for generating something different) and *improve* (i.e., aiming for something better). The degree of **modification**, on the other hand, conceptualizes the paradigm relationship between the input and output of GAI applications. The continuum reaches from *preserve* as a minimal change made by the GAI to *create* where the degree of *modification* significantly alters the input, thriving for novel results.

6. Conclusion, Limitations and Outlook

Due to the technological developments, AI is no longer just a theoretical construct, but an essential part of our professional and personal lives. The technology has even further evolved over the recent years to mainstream generative AI, a new type of AI which focuses on the creation and reimagination of content as well as the nearly human aspect as assistant in a wide variety of domains, including programming, sales, and accounting (Mondal et al., 2023).

While fundamental research on AI from technical, organizational, and social perspectives is a central part of the academic landscape, the topic area of GAI is currently unexplored. We address this deficiency and make **scientific contributions**: First, based on the analysis of 100 Generative AI applications, we provide a first conceptual outline for key dimensions and characteristics. Because the taxonomy we propose is not limited to a specific use case or domain (e.g., healthcare, accounting, etc.), it provides the foundation and potential for subsequent research to deepen GAI in dedicated domain areas. Second, we provide five types including a guiding framework that, in its entirety, can act as a conceptual foundation for other researchers to build their GAI concepts on.

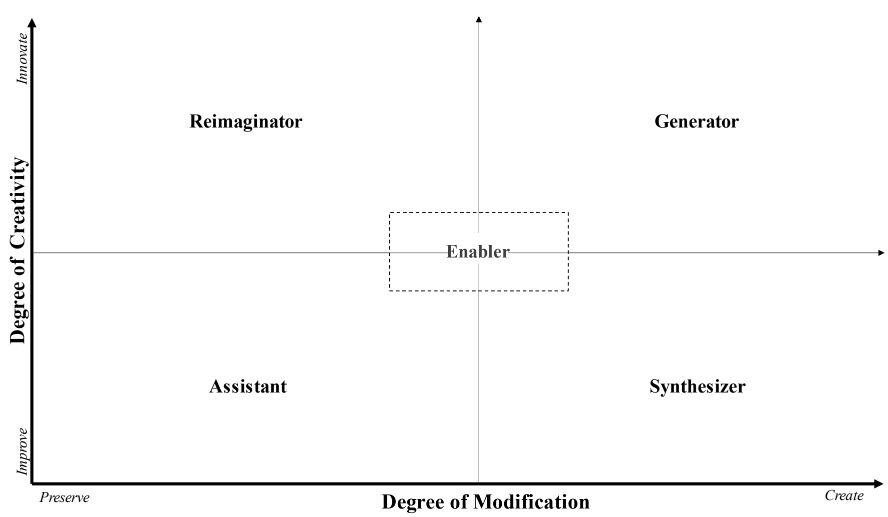

Figure 3. A Framework to Position the derived GAI Types

For practitioners, the research offers potential for developing and integrating GAI as well as repurposing existing applications based on the capability spectrum of the technology paradigm. The taxonomy serves as a tool for describing and analyzing existing GAI applications and as a medium for designing as well as configuring new applications. Each type represents a possible strategic option for managers to either optimize current applications or identify desired types and derive corresponding configurations in combination with the taxonomy. Managers can thus improve customer understanding, and derive specific strategic differences related to development, marketing, and integration.

Our results are subject to **limitations**. First, we derive the taxonomy and the typological framework with its types built on it exclusively from empirical real-world objects, which offers the possibility of integrating literature-based insights as they become available. Although the development of the framework and the typology was supported by quantitative data analysis, the data collection, and the derivation of the dimensions as characteristics is open to interpretation, and therefore other researchers may find divergent characteristics. This results in two implications for **future work.** Fundamentally relevant would be the theoretical grounding of the conceptual framework and generic types based on future appearing scientific literature. Furthermore, we suggest enriching the result artifacts with domain-specific knowledge (e.g., healthcare, software development) to develop associated models and deepen the body of knowledge on generative AI.

7. References

Ågerfalk, P. J. (2020). Artificial intelligence as digital agency. *European Journal of Information Systems*, *29*(1), 1–8. https://doi.org/10.1080/0960085X.2020.1721947

Aggarwal, A., Mittal, M., & Battineni, G. (2021). Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, *1*(1), 100004. https://doi.org/10.1016/j.jjimei.2020.100004

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Special Issue Editor's Comments: Managing Artificial Intelligence. *MIS Quarterly*, *45*(3), 1433–1450.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., . . . Amodei, D. (2020). Language Models are Few-Shot Learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, & H. Lin (Eds.), *Advances in Neural Information Processing Systems 33* (pp. 1877–1901). Curran Associates, Inc.

Brynjolfsson, E., Li, D [Danielle], & Raymond, L. (2023). *Generative AI at Work*. Cambridge, MA. https://doi.org/10.3386/w31161

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

Cooper, G. (2023). Examining Science Education in ChatGPT: An Exploratory Study of Generative Artificial Intelligence. *Journal of Science Education and Technology*, *32*(3), 444–452. https://doi.org/10.1007/s10956-023-10039-y

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Feng, Z., Guo, D., Tang, D., Duan, N., Feng, X., Gong, M., Shou, L., Qin, B., Liu, T., Jiang, D., & Zhou, M. (2020). CodeBERT: A Pre-Trained Model for Programming and Natural Languages. In T. Cohn, Y. He, & Y. Liu (Eds.), *Findings of the Association for Computational Linguistics: EMNLP 2020* (pp. 1536–1547). Association for Computational Linguistics. https://doi.org/10.18653/v1%2F2020.findings-emnlp.139

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with AI. *MIS Quarterly*, *45*(3), 1527–1556. https://doi.org/10.25300/MISQ/2021/16553

Gao, J., Shen, T., Wang, Z [Zian], Chen, W., Yin, K., Li, D [Daiqing], Litany, O., Gojcic, Z., & Fidler, S. (2022). GET3D: A Generative Model of High Quality 3D Textured Shapes Learned from Images. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, & A. Oh (Eds.), *Advances in Neural Information Processing Systems 35*. Curran Associates, Inc.

Generative AI. (n.d.). *Posts* [LinkedIn page]. LinkedIn. Retrieved June 13, 2023, from https://www.linkedin.com/company/genai-works/posts/?feedView=all

Gerlach, J., Werth, O., & Breitner, M. H. (2022). Artificial Intelligence for Cybersecurity: Towards Taxonomy-based Archetypes and Decision Support. *ICIS 2022 Proceedings,* Copenhagen, Denmark.

Geske, F., Hofmann, P., Lämmermann, L., Schlatt, V., & Urbach, N. (2021). Gateways to Artificial Intelligence:

Developing a Taxonomy for AI Service Platforms. *ECIS 2021 Research Papers,* Marrakech, Marocco.

Glass, R. L., & Vessey, I. (1995). Contemporary application-domain taxonomies. *IEEE Software*, *12*(4), 63–76. https://doi.org/10.1109/52.391837

Gm, H., Gourisaria, M. K., Pandey, M., & Rautaray, S. (2020). A comprehensive survey and analysis of generative models in machine learning. *Computer Science Review*, *38*, 100285. https://doi.org/10.1016/j.cosrev.2020.100285

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, *63*(11), 139–144. https://doi.org/10.1145/3422622

Gui, J., Sun, Z., Wen, Y., Tao, D., & Ye, J [Jieping] (2023). A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications. *IEEE Transactions on Knowledge and Data Engineering*, *35*(4), 3313–3332. https://doi.org/10.1109/TKDE.2021.3130191

Haase, J., & Hanel, P. H. P. (2023). *Artificial muses: Generative Artificial Intelligence Chatbots Have Risen to Human-Level Creativity. ArXiv.* https://doi.org/10.48550/arXiv.2303.12003

Hacker, P., Engel, A., & Mauer, M. (2023). Regulating ChatGPT and other Large Generative AI Models, *2023 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1112–1123). ACM. https://doi.org/10.1145/3593013.3594067

Heyder, T., & Posegga, O. (2021). Extending the foundations of AI literacy. *ICIS 2021 Proceedings,* Austin, Texas.

Ho, J., Jain, A [Ajay], & Abbeel, P. (2020). Denoising Diffusion Probabilistic Models. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, & H. Lin (Eds.), *Advances in Neural Information Processing Systems 33* (pp. 6840–6851). Curran Associates, Inc.

Hu, K. (2023, February 2). ChatGPT sets record for fastest-growing user base - analyst note. Reuters. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Huang, S. [@sonyatweetybird]. (2022, October 24). *As promised: here is our @sequoia Gen AI market map V2! Very thankful for the hundreds of folks who wrote in additions and edits. AI people are amazing* [Image attached] [Tweet]. Twitter. https://twitter.com/sonyatweetybird/status/1584580362339962880

Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering. *ACM Computing Surveys*, *31*(3), 264–323. https://doi.org/10.1145/331499.331504

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695. https://doi.org/10.1007/s12525-021-00475-2

Jebara, T. (2004). Generative Versus Discriminative Learning. In T. Jebara (Ed.), *Machine Learning* (pp. 17–60). Springer US. https://doi.org/10.1007/978-1-4419-9011-2_2

Kingma, D. P., & Welling, M. (2014). Auto-Encoding Variational Bayes. *Proceedings of the 2nd International Conference on Learning Representations 2014,* Banff, Canada.

Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., & Szopinski, D. (2022). An Update for Taxonomy Designers. *Business & Information Systems Engineering*, *64*(4), 421–439. https://doi.org/10.1007/s12599-021-00723-x

Kwon, G., & Ye, J. C. (2022). CLIPstyler: Image Style Transfer With a Single Text Condition. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 18062–18071). IEEE.

Lehmann, S., & Buxmann, P. (2009). Pricing Strategies of Software Vendors. *Business & Information Systems Engineering*, *1*(6), 452–462. https://doi.org/10.1007/s12599-009-0075-y

Liu, V. (2023). Beyond Text-to-Image: Multimodal Prompts to Explore Generative AI. In A. Schmidt, K. Väänänen, T. Goyal, P. O. Kristensson, & A. Peters (Eds.), *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–6). ACM. https://doi.org/10.1145/3544549.3577043

Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z [Ziang] (2023). ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology*, *74*(5), 570–581. https://doi.org/10.1002/asi.24750

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12. https://doi.org/10.1609/aimag.v27i4.1904

Midjourney. (n.d.). *Midjourney*. Retrieved May 23, 2023, from https://www.midjourney.com/

Mondal, S., Das, S., & Vrana, V. G. (2023). How to Bell the Cat? A Theoretical Review of Generative Artificial Intelligence towards Digital Disruption in All Walks of Life. *Technologies*, *11*(2), 44. https://doi.org/10.3390/technologies11020044

Nagasundaram, M., & Bostrom, R. P. (1994). The Structuring of Creative Processes Using GSS: A Framework for Research. *Journal of Management Information Systems*, *11*(3), 87–114. https://doi.org/10.1080/07421222.1994.11518051

Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), 336–359. https://doi.org/10.1057/ejis.2012.26

Noy, S., & Zhang, W. (2023). Experimental Evidence on the Productivity Effects of Generative Artificial

Intelligence. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.4375283

OpenAI. (2023). *GPT-4 Technical Report. ArXiv.* https://doi.org/10.48550/arXiv.2303.08774

Oppenlaender, J. (2022). The Creativity of Text-to-Image Generation, *Proceedings of the 25th International Academic Mindtrek Conference* (pp. 192–202). ACM. https://doi.org/10.1145/3569219.3569352

Pan, Z., Yu, W., Yi, X., Khan, A., Yuan, F., & Zheng, Y. (2019). Recent Progress on Generative Adversarial Networks (GANs): A Survey. *IEEE Access*, *7*, 36322–36333. https://doi.org/10.1109/ACCESS.2019.2905015

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199–3226. https://doi.org/10.1108/IJCHM-04-2020-0259

Poole, B., Jain, A [Ajay], Barron, J. T., & Mildenhall, B. (2023). DreamFusion: Text-to-3D using 2D Diffusion. *Proceedings of the Eleventh International Conference on Learning Representations,* Kigali, Rwanda.

Punj, G., & Stewart, D. W. (1983). Cluster Analysis in Marketing Research: Review and Suggestions for Application. *Journal of Marketing Research*, *20*(2), 134. https://doi.org/10.2307/3151680

Ramesh, A., Dhariwal, P., Nichol, A., Chu, C., & Chen, M. (2022). *Hierarchical Text-Conditional Image Generation with CLIP Latents. ArXiv.* https://doi.org/10.48550/arXiv.2204.06125

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-Resolution Image Synthesis with Latent Diffusion Models, *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 10674–10685). IEEE. https://doi.org/10.1109/CVPR52688.2022.01042

Schoormann, T., Möller, F., & Szopinski, D. (2022). Exploring Purposes of Using Taxonomies. *Wirtschaftsinformatik 2022 Proceedings,* Nuremburg, Germany.

Stevenson, C., Smal, I., Baas, M., Grasman, R., & van der Maas, H. (2022). Putting GPT-3's Creativity to the (Alternative Uses) Test. *ICCC'22 Proceedings,* Bolzano, Italy.

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus Effect of Generative AI: Charting the Path for Responsible Conduct of Scholarly Activities in Information Systems. *Information Systems Research*, *0*(0). https://doi.org/10.1287/isre.2023.ed.v34.n2

Szopinski, D., Schoormann, T., & Kundisch, D. (2019). BECAUSE YOUR TAXONOMY IS WORTH IT: TOWARDS A FRAMEWORK FOR TAXONOMY EVALUATION. *Proceedings of the 27th European Conference on Information Systems (ECIS),* Stockholm & Uppsala, Sweden.

Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science*, *361*(6404), 751–752. https://doi.org/10.1126/science.aat5991

Takagi, Y., & Nishimoto, S. (2023). High-Resolution Image Reconstruction With Latent Diffusion Models From Human Brain Activity. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 14453–14463). IEEE.

Teubner, T., Flath, C. M., Weinhardt, C., van der Aalst, W., & Hinz, O. (2023). Welcome to the Era of ChatGPT et al.: The Prospects of Large Language Models. *Business & Information Systems Engineering*, *65*, 95–101. https://doi.org/10.1007/s12599-023-00795-x

Tomczak, J. M. (2022). *Deep Generative Modeling*. Springer International Publishing. https://doi.org/10.1007/978-3-030-93158-2

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, \. u., & Polosukhin, I. (2017). Attention is All you Need. In I. Guyon, U. von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems 30* (pp. 5999–6009). Curran Associates, Inc.

Wang, H., Huang, J., & Zhang, Z. (2019). The Impact of Deep Learning on Organizational Agility. *ICIS 2019 Proceedings,* Munich, Germany.

Wei, R., & Mahmood, A. (2021). Recent Advances in Variational Autoencoders With Representation Learning for Biomedical Informatics: A Survey. *IEEE Access*, *9*, 4939–4956. https://doi.org/10.1109/ACCESS.2020.3048309

Weisz, J., Muller, M., He, J., & Houde, S. (2023). Toward General Design Principles for Generative AI Applications. *Joint Proceedings of the ACM IUI Workshops 2023,* Sydney, Australia.

Yin, R. K., & Campbell, D. T. (2018). *Case study research and applications: Design and methods* (Sixth edition). SAGE Publications, Inc.

Zeng, X. H., Vahdat, A., Williams, F., Gojcic, Z., Litany, O., Fidler, S., & Kreis, K. (2022). LION: Latent Point Diffusion Models for 3D Shape Generation. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, & A. Oh (Eds.), *Advances in Neural Information Processing Systems 35* (pp. 10021–10039). Curran Associates, Inc.