Generative AI in Business Process Optimization: A Maturity Analysis of Business Applications

Research Paper

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Abstract. Generative AI (GAI) holds enormous potential for companies. However, since the technology is relatively new, it remains unclear which areas can already benefit from its application and which fields require further research. This study provides managers and researchers with an overview of the value chain segmentsand business processes where GAI applications have been explored, proposed, or implemented in the scientific literature. For this purpose, a systematic literature review and a qualitative content analysis were conducted. The classification of applications took into account both the number of cases found and their maturity. GAIsystems in product development as well as maintenance and repair within manufacturing were among the most promising implementations. Within the value chain, the manufacturing segment exhibits the most mature use cases.

Keywords: *Generative AI, Business Processes, Optimization*

1 Introduction

Since the introduction of ChatGPT in November 2022, GAI has captivated public attention (OpenAI 2024; Marr 2023). A study by the investment bank Goldman Sachs highlights the potential impact GAI could have on society, suggesting a potential 7% increase in global GDP due to GAI, a remarkable achievement for a single technology (Elder 2023). However, as is common with new technologies, it is initially challenging to identify where GAI can be effectively applied and where it still lacks maturity(McAfee, et al. 2023). The scientific literature already contains reviews on GAI applications in areas such as supply chain management and manufacturing , as well as case studies on individual successful implementations of GAI systems (Jackson, et al. 2024; Zhang, et al. 2025; Kamnis 2023). However, there is a lack of a comprehensive systematic overview evaluating the maturity of use cases across all relevant business areas. In response to this gap, this study addresses the following research question: How mature are the use cases of generative AI for optimizing business processes, and which business areas have the strongest research backing?

To answer the research question, a systematic literature review was conducted. The statements from the publications were categorized using Mayring's qualitative content analysis. In evaluating the resulting category system, both the number and maturity of the use cases were considered. GAI use cases in product development as well as maintenance and repair within manufacturing were among the most successful categories. In terms of business areas, the manufacturing segment featured the most mature GAI implementations. The findings of this study offer researchers an overview of the emerging field of GAI in business processes and help identify promising directions for future research. For managers, the study offers insights into which business areas and processes can already benefit from GAI and where the technology remains immature.

The structure of the work begins with defining essential terms and explaining relevant concepts from the literature on GAI. Subsequently, the systematic literature review and qualitative content analysis as methods and their application within the context of this study are explained in more detail. The results are subsequently presented and discussed.

2 Scientific Foundation

2.1 Artificial Intelligence

The term artificial intelligence (AI) encompasses various algorithms capable of performing tasks that typically require human intelligence. This includes the understanding of natural language, recognizing patterns, and learning from experiences (Banh and Strobel 2023; Castelvecchi 2016; Winston 1993). Subcategories of AI include Machine Learning (ML), which involves developing algorithms that can solve problems independently by learning from data, and Deep Learning (DL), a special form of ML that uses neural networks to model data structures or recognize patterns in large datasets (Goodfellow, et al. 2016; Janiesch, et al. 2021; Samtani, et al. 2023). Neural networks are computer-generated models whose structure and function are inspired by the human brain (Goodfellow, et al. 2016).

2.2 Generative AI

GAI emerged from advances in DL, positioning it as a subcategory of DL. The key distinguishing feature of GAI from other forms of AI is its generative approach. García-Peñalvo and Vázquez-Ingelmo describe the operation of GAI as the creation of novel synthetic content across various forms to support various tasks (García-Peñalvo and Vázquez-Ingelmo 2023). In contrast, non-generative AI systems operate in a discriminative manner, processing data to recognize classifications, regressions, groupings, or decision boundaries (Banh and Strobel 2023). Regarding the technical implementation of this concept, four variants are predominantly used by scientists: Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), diffusion models, and Transformers (García-Peñalvo and Vázquez-Ingelmo 2023; Banh and Strobel 2023; Bengesi, et al. 2024). Other types that can function both generatively and discriminatively depending on training and architecture are recurrent neural networks (RNN), such as Long Short-Term Memory (LSTM) models (Yogatama, et al. 2017; Saka, et al.

2021). Two models presented in Chapter 4.1 as part of a use case are ChatGPT and Midjourney. ChatGPT is a GAI model based on the Transformer architecture and trained on large amounts of text data. It is thus classified as a Large Language Model (LLM). These have a human-like ability to understand and generate text (Teubner, et al. 2023). Midjourney is a GAI that can generate images from textual inputs. The exact architecture of Midjourney is not known, but it is suspected to be based on a diffusion model (Nikolenko 2023).

2.3 Generative AI in Business Process Management

Business Process Management (GPM) aims to design and control business processes so that organizations achieve their strategic and societal goals (Kampik, et al. 2024). Due to the versatility of GAI, promising approaches for its application have also emerged in this domain. For example, LLMs have been trained on process data to design and analyze processes (Beheshti, et al. 2023; Kampik, et al. 2024) or to automatically generate process models from text (Kourani, et al. 2024). In addition to LLMs, GANs have also contributed to process improvements (van Dun, et al. 2023). These recent research efforts demonstrate the significant potential of GAI for GPM.

3 Methodology

3.1 Systematic Literature Review

To address the research question, this study employed a systematic literature review as outlined by Tranfield, Denyer, and Smart (2003). This approach is preferred over the traditional literature review due to its reproducibility and transparency of results (Cook, et al. 1997; Hossain 2018; Tranfield, et al. 2003). A systematic literature review consists of six steps: 1) Formulation of the research question 2) Planning the approach 3) Literature search 4) Application of exclusion and inclusion criteria 5) Quality assessment 6) Synthesis of the literature (Jesson, et al. 2011). After formulating the research question, the scientific databases EBSCO, ProQuest, and Science Direct, which are among the mostcommonly used databases in management science, were searched (Tian, et al. 2018). The search terms used were "generative AI" AND "process optimization". Only peer-reviewed studies were considered, as these often hold a higher status within their research field (Podsakoff, et al. 2005). In Science Direct, there was also a restriction to "review articles" and "research articles". A total of 216 publications were found with these search criteria as of October 11, 2024.

In the next step, the titles of the studies were analyzed. The inclusion criterion was that ML or AI was considered in a context transferable to companies to specifically optimize one or more processes. Following this selection process, the number of relevant publications was reduced to 18. These were then read and analyzed in a further step. Studies that did not examine GAI as defined in this study or whose use cases were not transferable to companies were excluded. For studies detailing the GAI model, it was verified whether a GAN, VAE, Transformer, or diffusion model was employed.

RNNs and LSTMs were only considered if they operate generatively. All other models, according to the definition of this study, are not GAI systems. After applying the mentioned criteria, 12 publications remained. Five of these publications were literature analyses. Publications relevant to the study were included from these analyses according to the criteria mentioned above. The final publications included in the work amounted to 64 after applying the inclusion and exclusion criteria. Accordingly, a significant portion of the publications stems from literature analyses, which may lead to a potential overweighting of the topics covered in those analyses. Nevertheless, the approach was retained, as most studies included use cases spanning multiple categories. Furthermore, the evaluation did not focus on the number of publications discussing a particular use case, but rather on the total number of use case mentions across all publications, with a single paper potentially contributing multiple mentions.The analyzed publications are listed in the table of contents under "Analyzed Publications". The detailed list of statements can be made available upon request via email.

3.2 Qualitative Content Analysis

From the 64 publications, the relevant statements regarding use cases of GAI were first extracted and then analyzed. For the analysis, the qualitative content analysis according to Mayring (2000, 2014) was used, as it is suitable for the systematic and theoretically grounded reduction of large amounts of text data to their essence and is also a widely used methodology in the scientific literature (Mayring 2000; Hanelt, et al. 2021; Mayring 2014). The first step is the formation of categories. In this work, both deductive and inductive category formation were carried out. This approach is recommended by Mayring (2014) when the research question is suitably formulated (Mayring 2014).

To form the category system shown in Figure 1, the segments of the value chain according to Porter were first used deductively from the literature as categories to locate the applications in a business area (Porter and Millar 1985). In logistics, inbound and outbound logistics were combined because no relevant difference in the use of GAI in these areas could be determined. The operations segment in Porter’s value chain was renamed manufacturing, and only applications applicable to the physical production of products were considered within this segment. In Porter’s original work, this segment encompassed both the production of physical products as well as the services a company offers. This limitation of scope was necessary to ensure a clear separation from other areas of the value chain and to avoid duplicate assignments. In marketing companies, marketing activities would otherwise be assigned to both the operations segment, as they represent the actual product or service, and the marketing segment, as the companies market themselves. Furthermore, the category "cross-segment use cases" was added inductively to cover cases that can potentially be used in all segments of the value chain.

To enable a more detailed analysis, these supercategories were inductively assigned subcategories based on the identified use cases. These subcategories represent process areas that group a thematically homogeneous group of different business processes and are located in the thematic field of the supercategory. The formed subcategories can also be found in Figure 1. The decision to use process areas instead of individual business processes as subcategories is based on the fact that the same GAI use case can be used in several processes that are thematically similar. For example, a GAI in project management can create a schedule for the project and support the budget planning process. Therefore, the process area in which the GAI application is found, in this case, project management, was established as a subcategory to abstract several thematically similar processes to a higher level. Additionally, each use case was evaluated according to its maturity level. The categories were: successful implementation, partially successful implementation, unsuccessful implementation, promising research field, proposed research field, and no statement on maturity level. In this categorization, it was first examined whether the GAI use case was implemented and tested in practice, whereupon the category implementation was assigned. The gradations within the implementation category were based on whether the GAI system showed full, partial, or no success in the tested scenario. If a GAI use case was not practically implemented but was proposed as promising based on relevant arguments, the category research field was assigned. If the author mentioned successful technical implementations of similar use cases, for example, in another industry, the research field was classified as promising because concrete, transferable implementations already exist. If the argumentation was based solely on the theoretically explained properties of a G AI without referencing concrete implementations, it was classified as a proposed research field.

A total of 113 statements extracted from the 64 examined publications were assigned to categories based on their definitions, which were recorded in a coding guide. After a test run with 38 statements, about 30% of the entire subject of investigation, the category system was adjusted as Mayring (2014) also recommends (Mayring 2014). Here, the inductive formation of the category "cross-segment use cases" took place. The remaining statements were categorized into this final category system. The subcategories were continuously adjusted and expanded parallel to the categorization of the use cases into the supercategories.

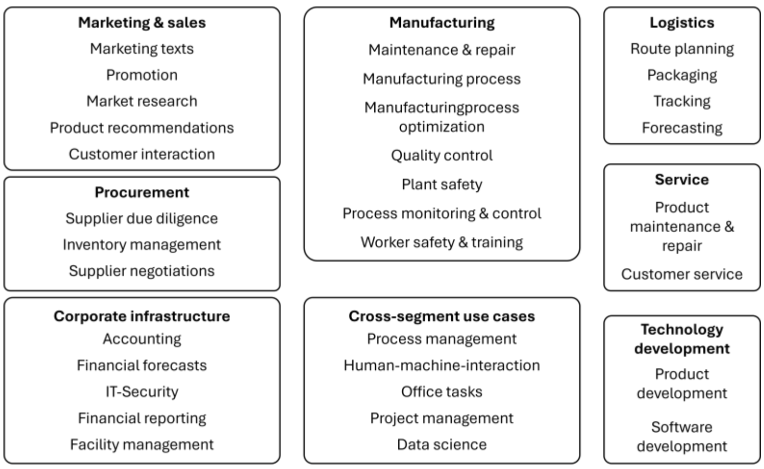

Figure 1: Category System

Mayring also prescribes a reliability check of the categories (Mayring 2014). For this purpose, the statements were coded by another economist familiar with the methodology. A Cohen's Kappa value of 0.772 was calculated from the two coded data sets, which, according to Landis and Koch (1977), represents a substantial agreement (Landis and Koch 1977). Thus, the procedure can be considered reliable. The check was only carried out for the supercategories, as the subcategories are very specific, and the assignment is therefore clearer.

3.3 Visualization

The extracted statements were visualized using a scatter plot in Jupyter Notebook. Each subcategory represents a point in the scatter plot. The X-axis counts the number of use cases found that were assigned to the corresponding subcategory. The Y-axis represents the average maturity level of all use cases in the subcategory. For this purpose, the maturity levels mentioned above were assigned values from 0-3 according to Table 1. To facilitate a structured discussion of the results, the diagram was divided into quadrants Q1 to Q4: Q1 includes process areas with a high maturity level of 1.5–3 and at least eight use cases, Q2 the same maturity levels but with fewer than eight instances. Q3 contains areas with a low maturity level of 0–1.5 and fewer than eight cases, Q4 those with more than eight. Additionally, a minimal, random-based deviation of the point positions was allowed due to overlapping process areas. This enhances clarity, but it is important to note that the point positions are approximate for interpretation. Additionally, numbers were added in areas with overlapping data points

Table 1. Maturity Level System

Maturity Level	Numerical Value
Successful Implementation	3
Partially Successful Implementation	2
Unsuccessful Implementation	0
Promising Research Field	2
Proposed Research Field	1
No Statement on Maturity Level	1

Furthermore, a bar chart was created to depict the number of actually implemented use cases per process area. Research fields and applications without statements on the maturity level were excluded.

4 Results

4.1 Mature and Strongly Implemented Process and Business Areas

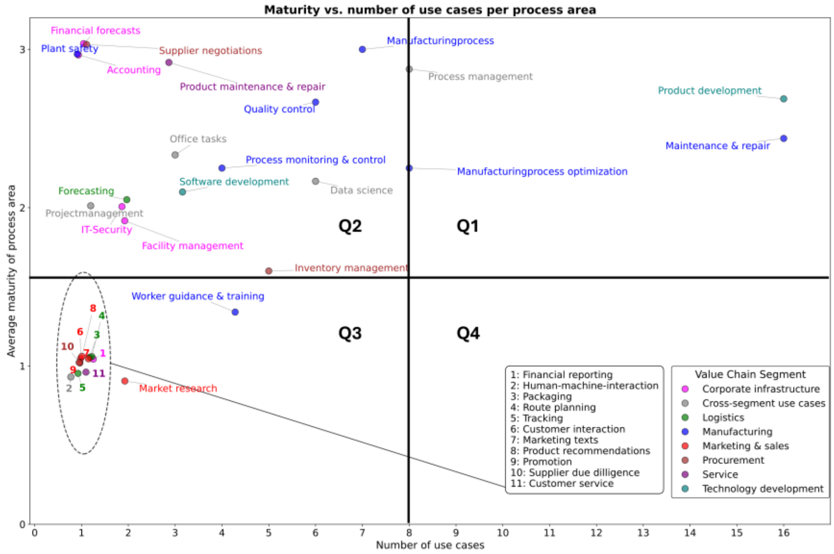

Figure 2. Scatter Diagram

Quadrant Q1 of the scatter diagram in Figure 2 is most relevant for identifying mature and well-researched GAI applications in process areas. Since Q1 already includes areas with frequent successful implementations, the most mature application fields for G AI are located here. The two most developed process categories in this quadrant are product development and maintenance in manufacturing processes. In product development, there is a wide range of applications, such as supporting engineers with expert systems and generating product designs based on technical specifications. Many applications were found in the area of optical product design. Six studies address GAI systems that support the optical design process (Deng, et al. 2023; Radhakrishnan, et al. 2018; Makatura, et al. 2023; Yin, et al. 2023; Wu, et al. 2024; Xu, et al. 2024b). All applications were successfully implemented, ranging from creating design proposals to facilitating collaboration between designers. One publication, for example, presents an implementation that integrates AI models such as ChatGPT and Midjourney. In the use case, ChatGPT is first used to generate adjectives that capture consumers' emotional responses to the design. Midjourney then creates a target design from these adjectives. Subsequently, various colored versions of the target design are created with the help of AI. Based on color harmony theory, the optimal color combination is then selected (Wu, et al. 2024). Other applications in product development focus, among other things, on the technical aspects of product design (Fritsche, et al. 2020; Decardi-Nelson, et al. 2024; Kamnis 2023; Yang, et al. 2023). In maintenance, a common application is training ML models, which are used for early damage detection of production machines, with GANs. Collecting data for training these ML models is often time-consuming and difficult. Particularly, data on machine failures are rare and hard to find in large quantities, as failures rarely occur (Liu, et al. 2022). The performance of ML models in damage detection is significantly influenced by the quality and quantity of training data. Specifically, one-sided training with predominantly healthy operational data and few datasets of damage cases is a widespread problem. GANs can be trained on a small set of damage data to generate synthetic datasets that closely resemble real data in authenticity. This allows a substantial amount of training data for ML models to be generated from a small dataset. GAN systems can thus significantly accelerate and enhance the training of these ML models (Liu, et al. 2022; Zhou, et al. 2017). This application was identified in five instances, each successfully implemented (Wang, et al. 2018; Gao, et al. 2024; Shao, et al. 2019; Liu, et al. 2022; Decardi-Nelson, et al. 2024). Even when considering practical implementations in Figure 3, these two areas were leading. Other promising application fields are process management and optimization of manufacturing processes.

Quadrant Q2 includes areas that show promise due to individual successful implementations or positive results in comparable application domains but have not been as thoroughly researched as those in Q1. Applications in the manufacturing process and quality control are the most successful representatives of this quadrant. These areas could soon rise to Quadrant Q1.

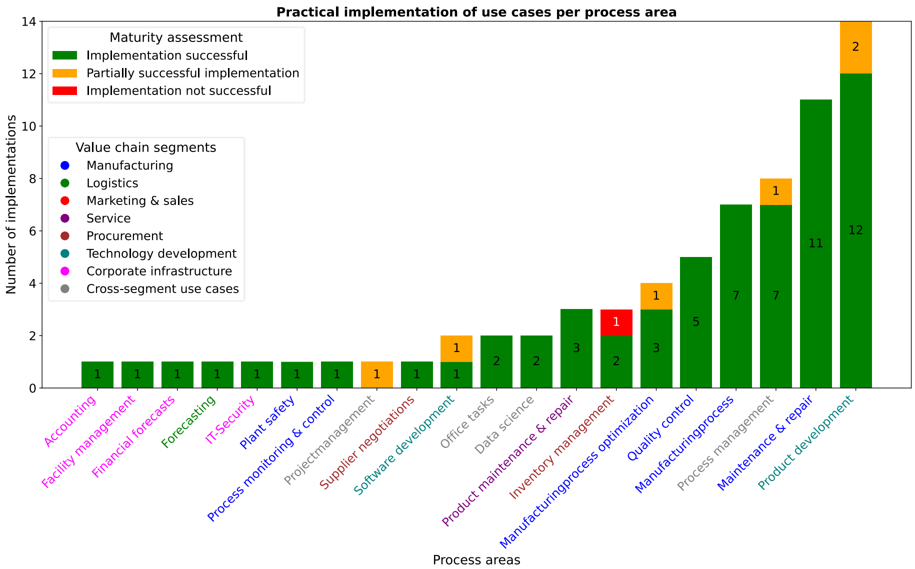

Figure 3. Bar Diagram

Overall, applications in the manufacturing area have been extensively studied and effectively implemented. With the exception of employee guidance and training, all process areas in the manufacturing environment are located in the top two quadrants and thus have a high maturity level. Among the six strongest implementation areas in Figure 3, four areas are located in the manufacturing environment.

4.2 Less Researched and Weakly Implemented Process and Business Areas

The lower left area Q3 includes process areas predominantly discussed in theoretical terms or only proposed. Process areas where individual practical implementations were unsuccessful would also be located here. However, an unsuccessful implementation was only found once. Notably, many process areas have only a single use case with a maturity level of one. Looking at the value chain segments, it can be observed that all process areas within the marketing and sales segment are found in this area.

Q4 would include process areas where applications were frequently implemented yet were unsuccessful, or frequently discussed but never practically implemented. However, this quadrant currently contains no process areas. It is important to note that no applications were identified in the human resources segment.

5 Discussion of Results

5.1 Commonalities of Mature Process Areas and Implementations

The most advanced application fields identified in the study were product development, maintenance and repair, process management, manufacturing process optimization, manufacturing processes, and quality control. A clear commonality among these areas is their predominantly technical nature. Process areas where interpersonal interactions dominate or are primarily situated in the business environment, such as accounting or customer interaction processes in marketing or sales, are underrepresented. This could be because employees in technical domains are more intensively engaged with new technologies, as evaluating technological advancements is part of their job scope. Additionally, AI systems have been in use in these technical areas for a long time, providing employees with experience with the technology. For other process areas, such as writing advertising copy, AI only became relevant with the introduction of ChatGPT in 2022 (Marr 2023; OpenAI 2024). Furthermore, employees in these areas generally use fewer technologies in their work and tend to be less IT-savvy, which may result in these areas lagging behind in the adoption of new technologies compared to technical domains. These domain-specific characteristics could also influence academic research, possibly leading researchers in technical fields to have been publishing on GAI systems for a longer time.

Regarding the use cases assigned to the successful process areas, it is noticeable that many fundamentally deal with the analysis and subsequent context-specific interpretation of large data sets. This capability of G AI can be applied differently across areas. By analyzing textual data, for example, process knowledge databases can be created, or technical questions in maintenance or product development can be answered. Production or sensor data can also be analyzed and interpreted with GAI. Of the 49 use cases identified in these process areas, 28 focus on data analysis and interpretation. Since the most successful process areas are technical in nature, this commonality is logical, as data analysis and interpretation is a relevant topic for this domain.

Looking at the GAI models, it becomes evident that GAN models have particularly many successful implementations. All 21 use cases for GAN systems found in the study were successfully implemented. The exceptionally high maturity of these models could be partly due to the fact that GANs were developed as early as 2014 (Goodfellow, et al. 2014). Most of the other studies, on the other hand, use ChatGPT, which was only introduced in 2022, meaning many use cases have not yet been sufficiently investigated or exist only as proposals (Marr 2023; OpenAI 2024).

5.2 Low Implementation Strength in Many Process Areas

Of all the process areas, only four made it into Quadrant Q1, indicating a high level of maturity and frequent mentions. Additionally, no process areas could be identified in Q4, where areas with many mentions and low maturity are grouped. This suggests that the research field of G AI in terms of process optimization is still in its nascent stages. This is also evident when looking at the publication dates of the studies considered. The oldest publication dates back to 2017, and only 20 of the 64 studies considered were published before 2022. This observation is not surprising, as many studies use the relatively new system ChatGPT as GAI (Marr 2023; OpenAI 2024). This might also explain why no areas were identified in Q4 and only one unsuccessful use case was documented. Currently, there are simply too few concrete implementations to identify a significant number of failed applications.

At the same time, it offers an explanation for why many process areas were mentioned only once as a research field or proposal without concrete implementation and are therefore closely located in Quadrant Q3. The research field is very young, which is reflected in the maturity level and the number of use cases found. However, the use cases in Q3 should not be perceived as unpromising. Currently, there are insufficient statements in the literature to make a well-founded assessment of certain areas. An alternative explanation for the lack of failed implementations, in particular, could be the so-called "publication bias" (Field and Gillett 2010; Rosenthal 1979). Studies that could not demonstrate significant effects or positive results are not published as frequently as studies that could demonstrate an effect. This results in a bias in the published literature in favor of significant effects or, in the case of this study, successful implementations (Dickersin, et al. 1992; Field and Gillett 2010; Greenwald 1975).

6 Conclusion and Implications

Contribution to Theory and Practice. On the theoretical side, this work synthesizes findings from various individual studies on the topic of GAI in business processes, offering an overview of areas where research has already made significant progress and those requiring further attention. Process areas in Q2 are particularly compelling for researchers, as initial successes have been achieved, and further work can significantly contribute to their development towards implementation in companies. Q3 also serves as a valuable resource for researchers exploring less examined but promising GAI application fields. For industry managers, Quadrant Q1 offers a reliable indication of which process areas GAI already possesses the necessary maturity for industry rollout. Simultaneously, managers should continuously seek new applications, as the field is still young and can develop significantly in a short time. Applications with the greatest long-term potential may currently exhibit low maturity levels but have the capacity for significant development in the coming years.

Limitations. Although a systematic literature review was conducted, other researchers may discover additional publications when exploring the research question or classify the found literature differently regarding the selection criteria. Bartels and Reinders (2011) and Greenhalgh et al. (2004) assume that this limitation realistically occurs in every literature review. To counteract this limitation, the methodology was described and justified in detail to ensure reproducibility. However, it is assumed that this study was limited to analyzing a subset of the available literature. Furthermore, the aforementioned publication bias should be noted, as this study is limited to published studies. A potential bias in favor of successful implementations should be considered when interpreting the results.

Further Research Fields. A promising avenue for research involves quantifying the benefits of GAI applications, for example, in the form of monetary savings through case studies, to enable a more objective assessment of the value contribution of the process areas. This consideration would provide managers with an even more detailed insight into the most promising application fields of GAI. In terms of value chain segments, marketing and sales emerge as promising areas for future research. In this segment, various proposals for GAI applications can be found, but there is a lack of technical implementations, as evidenced by the consistently low maturity level of the process areas assigned to this field. Since marketing and sales activities also offer excellent opportunities to measure success, for example through likes on social media posts or conversion rates from prospects to buyers, practical work in this area could provide clarity on the effectiveness of GAI in this research field. Another potential research area is human resource management, as no literature on this topic was found in the context of this work, thus representing a poorly researched area.

Conclusion. The integration of GAI into business processes is an emerging field with substantial potential. According to the research question, when examining the scientific literature, it can be determined that applications in the process areas of maintenance and repair, as well as product development, are particularly well-developed. Regarding company areas, the field of manufacturing stands out with many use cases with a high maturity level as particularly well-researched. At the same time, research in many other processes and company areas is still in its nascent stages. Thus, advancing research in this direction is essential for evaluating GAI applications using scientific methods and providing both researchers and practitioners with a sound basis for decision-making.

References

Analyzed Publications

Ahmad, A., et al. (2023), Towards Human-Bot Collaborative Software Architecting with ChatGPT, in, ‘EASE '23: The International Conference on Evaluation and Assessment in Software Engineering’, ACM, S. 279–285.

Akhtar, P., et al. (2024), ‘Smart product platforming powered by AI and generative AI: Personalization for the circular economy’, International Journal of Production Economics 273, S. 109283.

Badini, S., et al. (2023), ‘Assessing the capabilities of ChatGPT to improve additive manufacturing troubleshooting’, Advanced Industrial and Engineering Polymer Research 6(3), S. 278–287.

Barcaui, A., Monat, A. (2023), ‘Who is better in project planning? Generative artificial intelligence or project managers?’, Project Leadership and Society 4, S. 100101.

Camargo, M., Dumas, M., González-Rojas, O. (2022), Learning Accurate Business Process Simulation Models from Event Logs via Automated Process Discovery and Deep Learning, in, Advanced Information Systems Engineering, Springer International Publishing, S. 55–71.

Cao, S., et al. (2018), Application of Generative Adversarial Networks for Intelligent Fault Diagnosis, in, ‘2018 IEEE 14th International Conference on Automation Science and Engineering (CASE)’, IEEE, S. 711–715.

Chhetri, S. R., et al. (2019), GAN-Sec: Generative Adversarial Network Modeling for the Security Analysis of Cyber-Physical Production Systems, in, ‘2019 Design, Automation & Test in Europe Conference & Exhibition (DATE)’, IEEE, S. 770–775.

Cooper, C., et al. (2020), ‘Anomaly detection in milling tools using acoustic signals and generative adversarial networks’, Procedia Manufacturing 48, S. 372–378.

Decardi-Nelson, B., et al. (2024), ‘Generative AI and process systems engineering: The next frontier’, Computers & Chemical Engineering 187, S. 108723.

Deng, Z., et al. (2023), ‘Bionic Design Model for Co-creative Product Innovation Based on Deep Generative and BID’, International Journal of Computational Intelligence Systems 16(1), S. 8.

Evermann, J., Rehse, J.-R., Fettke, P. (2017), ‘Predicting process behaviour using deep learning’, Decision Support Systems 100, S. 129–140.

Fan, H., et al. (2024), ‘Embodied intelligence in manufacturing: leveraging large language models for autonomous industrial robotics’, Journal of Intelligent Manufacturing 36(2), S. 1141–1157.

Fritsche, M., et al. (2020), Numerical Performance Predictions of Artificial Intelligence-Driven Centrifugal Compressor Designs, in, ‘ASME 2020 Fluids EngineeringDivision Summer Meeting collocated with the ASME 2020 Heat Transfer Summer Conference and the ASME 2020 18th International Conference on Nanochannels, Microchannels, and Minichannels', American Society of Mechanical Engineers.

Gao, R., et al. (2024), 'Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions', CIRP Annals 73(2), S. 723–749.

Gilardi, F., Alizadeh, M., Kubli, M. (2023), 'ChatGPT outperforms crowd workers for text-annotation tasks', Proceedings of the National Academy of Sciences of the United States of America 120(30), S. 1-14.

Gkournelos, C., Konstantinou, C., Makris, S. (2024), 'An LLM-based approach for enabling seamless Human-Robot collaboration in assembly', CIRP Annals 73(1), S. 9–12.

Guo, L., et al. (2022), 'An automatic method for constructing machining process knowledge base from knowledge graph', Robotics and Computer-Integrated Manufacturing 73, S. 102222.

Hanga, K. M., Kovalchuk, Y., Gaber, M. M. (2020), 'A Graph-Based Approach to Interpreting Recurrent Neural Networks in Process Mining', IEEE Access 8, S. 172923–172938.

Haninger, K., Garcia, R. V., Krueger, J. (2020), https://doi.org/10.48550/arXiv.2011.09906. Zuletzt geprüft am: 10.12.2024.

Hassani, H., Silva, E. S. (2023), 'The Role of ChatGPT in Data Science: How AI-Assisted Conversational Interfaces Are Revolutionizing the Field', Big Data and Cognitive Computing 7(2), S. 62.

Jackson, I., et al. (2024), 'Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation', International Journal of Production Research 62(17), S. 6120–6145.

Javaid, M., Haleem, A., Singh, R. P. (2023), 'A study on ChatGPT for Industry 4.0: Background, potentials, challenges, and eventualities', Journal of Economy and Technology 1, S. 127–143.

Jia, J., et al. (2022), Diagnosis of power operation and maintenance records based on pre-training model and prompt learning, in, '2022 21st International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES)', IEEE, S. 58–61.

Jiang, F., et al. (2024), Research on Failure Cause Analysis Method Based on Aircraft Maintenance Records, in, Proceedings of the 6th China Aeronautical Science and Technology Conference, Springer Nature Singapore, S. 374–388.

Jiang, Y., et al. (2023), VIMA: robot manipulation with multimodal prompts, in, 'ICML'23: International Conference on Machine Learning', JMLR.org, S. 14975–15022.Kamnis, S. (2023), 'Generative pre-trained transformers (GPT) for surface engineering', Surface and Coatings Technology 466, S. 129680.

Kmiecik, M. (2023), 'ChatGPT in third-party logistics – The game-changer or a step into the unknown?', Journal of Open Innovation: Technology, Market, and Complexity 9(4), S. 100174.

Krajsic, P., Franczyk, B. (2021), Variational Autoencoder for Anomaly Detection in Event Data in Online Process Mining, in, '23rd International Conference on Enterprise Information Systems', SCITEPRESS - Science and Technology Publications, S. 567–574.

Lee, H., Kang, S., Chung, K. (2022), 'Robust Data Augmentation Generative Adversarial Network for Object Detection', Sensors 23(1), S. 157.

Liu, L., et al. (2019), 'Defective samples simulation through adversarial training for automatic surface inspection', Neurocomputing 360, S. 230–245.

Liu, P., et al. (2024), 'Joint Knowledge Graph and Large Language Model for Fault Diagnosis and Its Application in Aviation Assembly', IEEE Transactions on Industrial Informatics 20(6), S. 8160–8169.

Liu, S., et al. (2022), 'Data synthesis using deep feature enhanced generative adversarial networks for rolling bearing imbalanced fault diagnosis', Mechanical Systems and Signal Processing 163, S. 108139.

Liu, X., et al. (2023), Performance of ChatGPT on CMRP: Potential for Assisting Maintenance and Reliability Professionals Using Large Language Models, in, 'IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society', IEEE, S. 1–7.

Lo, W., et al. (2024), 'Increased Productivity and Reduced Waste with Robotic Process Automation and Generative AI-powered IoE Services', Journal of Web Engineering 23(1), S. 53–88.

Makatura, L., et al. (2023), 'How Can Large Language Models Help Humans in Design and Manufacturing?', Harvard Data Science Review.

Nguyen, H. T. C., et al. (2019), 'Autoencoders for improving quality of process event logs', Expert Systems with Applications 131, S. 132–147.

Noy, S., Zhang, W. (2023), 'Experimental evidence on the productivity effects of generative artificial intelligence', Science 381(6654), S. 187–192.

Park, G., Song, M. (2020), 'Predicting performances in business processes using deep neural networks', Decision Support Systems 129, S. 113191.

Qin, X., et al. (2023), An effective knowledge mining method for compressor fault text data based on large language model, in, '2023 International Conference on Computer Science and Automation Technology (CSAT)', S. 44–48.Radhakrishnan, S., et al. (2018), Creative Intelligence – Automating Car Design Studio with Generative Adversarial Networks (GAN), in, Machine Learning and Knowledge Extraction, Springer International Publishing, S. 160–175.

Rane, N., Choudhary, S., Rane, J. (2024), 'Intelligent Manufacturing through Generative Artificial Intelligence, Such as ChatGPT or Bard', SSRN Electronic Journal.

Rao, K., et al. (2020), RL-CycleGAN: Reinforcement Learning Aware Simulation-to-

Real, in, 'IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)', IEEE, S. 11154–11163.

Shao, S., Wang, P., Yan, R. (2019), 'Generative adversarial networks for data augmentation in machine fault diagnosis', Computers in Industry 106, S. 85–93.

Takahashi, S., Chen, Y., Tanaka-Ishii, K. (2019), 'Modeling financial time-series with generative adversarial networks', Physica A: Statistical Mechanics and its Applications 527, S. 121261.

Taymouri, F., et al. (2020), Predictive Business Process Monitoring via Generative Adversarial Nets: The Case of Next Event Prediction, in, Business Process Management, Springer International Publishing, S. 237–256.

Theis, J., Darabi, H. (2020), 'Adversarial System Variant Approximation to Quantify Process Model Generalization', IEEE Access 8, S. 194410–194427.

Tian, C., et al. (2019), 'Data driven parallel prediction of building energy consumption using generative adversarial nets', Energy and Buildings 186, S. 230–243.
van Hoek, R., et al. (2022), 'How Walmart Automated Supplier Negotiations', Harvard Business Review.

Vlassis, N., Sun, W. (2023), 'Denoising diffusion algorithm for inverse design of microstructures with fine-tuned nonlinear material properties', Computer Methods in Applied Mechanics and Engineering 413, S. 116126.

Wang, H., Li, Y.-F. (2023), Large Language Model Empowered by Domain-Specific Knowledge Base for Industrial Equipment Operation and Maintenance, in, '2023 5th International Conference on System Reliability and Safety Engineering (SRSE)', IEEE, S. 474–479.

Wang, P., Karigiannis, J., Gao, R. (2024), 'Ontology-integrated tuning of large language model for intelligent maintenance', CIRP Annals 73(1), S. 361–364.

Wang, Y., Vinogradov, A. (2023), 'Improving the Performance of Convolutional GAN Using History-State Ensemble for Unsupervised Early Fault Detection with Acoustic Emission Signals', Applied Sciences 13(5), S. 3136.

Wang, Z., Wang, J., Wang, Y. (2018), 'An intelligent diagnosis scheme based on generative adversarial learning deep neural networks and its application to planetary gearbox fault pattern recognition', Neurocomputing 310, S. 213–222.Wu, F., Hsiao, S.-W., Lu, P. (2024), 'An AIGC-empowered methodology to product color matching design', Displays 81, S. 102623.

Xiao, Y., et al. (2023), 'Knowledge graph-based manufacturing process planning: A state-of-the-art review', Journal of Manufacturing Systems 70, S. 417–435.

Xu, D., et al. (2021), 'Improving exploration efficiency of deep reinforcement learning through samples produced by generative model', Expert Systems with Applications 185, S. 115680.

Xu, M., et al. (2023), 'Generative AI-Empowered Simulation for Autonomous Driving in Vehicular Mixed Reality Metaverses', IEEE Journal of Selected Topics in Signal Processing 17(5), S. 1064–1079.

Xu, Q., et al. (2024a), 'Generative AI and DT integrated intelligent process planning: a conceptual framework', International Journal of Advanced Manufacturing Technology 133, S. 2461–2485.

Xu, S., et al. (2024b), 'LLM enabled generative collaborative design in a mixed reality environment', Journal of Manufacturing Systems 74, S. 703–715.

Yang, K., et al. (2023), 'A new design approach of hardware implementation through natural language entry', IET Collaborative Intelligent Manufacturing 5(4).

Yin, H., Zhang, Z., Liu, Y. (2023), 'The Exploration of Integrating the Midjourney Artificial Intelligence Generated Content Tool into Design Systems to Direct Designers towards Future-Oriented Innovation', Systems 11(12), S. 566.

You, H., et al. (2023), 'Robot-Enabled Construction Assembly with Automated Sequence Planning Based on ChatGPT: RoboGPT', Buildings 13(7), S. 1772.

Zhang, C., et al. (2025), 'A survey on potentials, pathways and challenges of large language models in new-generation intelligent manufacturing', Robotics and Computer-Integrated Manufacturing 92, S. 102883.

Zhou, B., et al. (2024), 'CausalKGPT: Industrial structure causal knowledge-enhanced large language model for cause analysis of quality problems in aerospace product manufacturing', Advanced Engineering Informatics 59, S. 102333.

Cited Literature

Banh, L., Strobel, G. (2023), 'Generative artificial intelligence', Electronic Markets 33(1), S. 1–17.

Bartels, J., Reinders, M. (2011), 'Consumer innovativeness and its correlates: A propositional inventory for future research', Journal of Business Research 64(6), S. 601–609.

Beheshti, A., et al. (2023), ProcessGPT: Transforming Business Process Management with Generative Artificial Intelligence, in, '2023 IEEE International Conference on Web Services (ICWS)', IEEE, S. 731–739.Bengesi, S., et al. (2024), 'Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers', IEEE Access 12, S. 69812–69837.

Castelvecchi, D. (2016), 'Can we open the black box of AI?', Nature 538(7623), S. 20–23.

Cook, D., Mulrow, C., Haynes, B. (1997), 'Systematic reviews: synthesis of best evidence for clinical decisions', Annals of internal medicine 126(5), S. 376–380.

Dickersin, K., Min, Y., Meinert, C. (1992), 'Factors influencing publication of research results. Follow-up of applications submitted to two institutional review boards', The Journal of the American Medical Association 267(3), S. 374–378.

Elder, B. (2023), https://www.ft.com/content/50b15701-855a-4788-9a4b-5a0a9ee10561. Zuletzt geprüft am: 27.11.2024.

Field, A., Gillett, R. (2010), 'How to do a meta-analysis. The British journal of mathematical and statistical psychology', The British journal of mathematical and statistical psychology 63(3), S. 665–694.

García-Peñalvo, F., Vázquez-Ingelmo, A. (2023), 'What Do We Mean by GenAI? A Systematic Mapping of The Evolution, Trends, and Techniques Involved in Generative AI', International Journal of Interactive Multimedia and Artificial Intelligence 8(4), S. 7–16.

Goodfellow, I., et al. (2014), 'Generative Adversarial Networks', Advances in Neural Information Processing Systems 3(11), S. 1–9.

Goodfellow, I., Courville, A., Bengio, Y. (2016), Deep learning. The MIT Press.

Greenhalgh, T., et al. (2004), 'Diffusion of innovations in service organizations: systematic review and recommendations', The Milbank quarterly 82(4), S. 581–629.

Greenwald, A. (1975), 'Consequences of prejudice against the null hypothesis', Psychological Bulletin 82(1), S. 1–20.

Hanelt, A., et al. (2021), 'A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change', Journal of Management Studies 58(5), S. 1159–1197.

Hossain, M. (2018), 'Frugal innovation: A review and research agenda', Journal of Cleaner Production 182, S. 926–936.

Janiesch, C., Zschech, P., Heinrich, K. (2021), 'Machine learning and deep learning', Electronic Markets 31(3), S. 685–695.

Jesson, J., Matheson, L., Lacey, F. (2011), Doing your literature review. SAGE.

Kampik, T., et al. (2024), 'Large Process Models: A Vision for Business Process Management in the Age of Generative AI', KI - Künstliche Intelligenz.Kourani, H., et al. (2024), ProMoAI: Process Modeling with Generative AI, in,
'IJCAI 2024: 33rd International Joint Conference on Artificial Intelligence 2024', S. 8708–8712.

Landis, R., Koch, G. (1977), 'The Measurement of Observer Agreement for Categorical Data', Biometrics 33(1), S. 159–174.

Marr, B. (2023), https://www.forbes.com/sites/bernardmarr/2023/05/19/a-short-history-of-chatgpt-how-we-got-to-where-we-are-today/. Zuletzt geprüft am: 06.12.2024.

Mayring, P. (2000), 'Qualitative Content Analysis', Forum: Qualitative Social Research 1(2).

Mayring, P. (2014), Qualitative content analysis: theoretical foundation, basic procedures and software solution.

McAfee, A., Rock, D., Brynjolfsson, E. (2023), ‘How to Capitalize on Generative AI’, Harvard Business Review.

Nikolenko, S. (2023), https://synthesis.ai/2023/08/09/generative-ai-vi-stable-diffusion-dall-e-2-and-midjourney/. Zuletzt geprüft am: 04.12.2024.
OpenAI (2024), https://help.openai.com/en/articles/6825453-chatgpt-release-notes. Zuletzt geprüft am: 27.11.2024.

Podsakoff, P., et al. (2005), ‘The influence of management journals in the 1980s and 1990s’, Strategic Management Journal 26(5), S. 473–488.

Porter, M., Millar, V. (1985), ‘How Information Gives You Competitive Advantage’, Harvard Business Review 63(4), S. 149–160.
Rosenthal, R. (1979), ‘The file drawer problem and tolerance for null results’, Psychological Bulletin 86(3), S. 638–641.

Saka, K., et al. (2021), ‘Antibody design using LSTM based deep generative model from phage display library for affinity maturation’, Scientific reports 11(1), S. 5852.

Samtani, S., et al. (2023), ‘Deep Learning for Information Systems Research’, Journal of Management Information Systems 40(1), S. 271–301.
Teubner, T., et al. (2023), ‘Welcome to the Era of ChatGPT et al’, Business & Information Systems Engineering 65(2), S. 95–101.

Tian, M., et al. (2018), ‘How does culture influence innovation? A systematic literature review’, Management Decision 56(5), S. 1088–1107.

Tranfield, D., Denyer, D., Smart, P. (2003), ‘Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review’, British Journal of Management 14(3), S. 207–222.
van Dun, C., et al. (2023), ‘ProcessGAN: Supporting the creation of business process improvement ideas through generative machine learning’, Decision Support Systems 165, S. 113880.Winston, P. (1993), Artificial intelligence. Addison-Wesley.

Yogatama, D., et al. (2017), https://doi.org/10.48550/arXiv.1703.01898. Zuletzt geprüft am: 14.12.2024.

Zhou, P., et al. (2017), ‘Online feature selection for high-dimensional class-imbalanced data’, Knowledge-Based Systems 136, S. 187–199.