Applications of Generative AI in the Product Development Process: A Scoping Review

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Abstract

Generative Artificial Intelligence is revolutionizing industries such as software development and holds promise for transforming digital engineering, product development, and the entire product life cycle. This study reviews 22 documented use cases where GenAI enhances different stages of the product life cycle, emphasizing its potential to drive cost efficiencies, accelerate time to market, and enhance customization capabilities. By synthesizing findings from academic databases, grey literature, and expert insights this paper provides a first comprehensive overview of GenAI's emerging applications in industrial settings, aggregating opportunities, and challenges in its adoption. We conclude that emerging use cases of GenAI in digital engineering emphasize the need for further investigation.

Keywords

generative artificial intelligence, product development, digital engineering

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1. Introduction

Generative Artificial Intelligence (GenAI) is a rapidly advancing field impacting creative arts, medicine, education, and global economies. The advent of the transformer model [1], coupled with pre-training and accessibility to vast datasets [2], has driven breakthroughs across various domains. While certain areas, such as software development, have shown substantial productivity gains by employing GenAI tools [3], the potential for similar improvements in digital engineering and virtual product development is a compelling frontier to explore.

Automating product development via GenAI holds substantial promise for cost reduction and enhanced industrial productivity. Its integration can become crucial for global economic advancement and prosperity. The effective deployment of AI in product development can accelerate time to market, alleviate shortages of skilled labor, and augment user customization capabilities [4]. Moreover, the market demand for shorter lead times [5], cost efficiencies, and adherence to quality management standards underscore the urgent need for AI-driven automation. We currently often encounter overly enthusiastic claims about GenAI's potential benefits, because of the promised economic advantages.

The primary goal in this work is to remove the exaggerations, and vague promises currently surrounding GenAI and establish a comprehensive overview of where GenAI can be applied not just in digital engineering and product development, but along the entire product life cycle. To achieve this, we have formulated two specific research questions:

1. Which applications of GenAI in the product life cycle and the product development process and their distinct stages are documented?
2. Which GenAI capability could support in which stage of the product life cycle?

By answering these questions, we aim to provide a methodological overview of GenAI applications within the product life cycle (PLC) and product development process (PDP), contributing to understanding the potential of GenAI in digital engineering.

Figure 1: The steps of the PDP in green are a subset of the PLC in blue and green [6].

2. Background

2.1. Product Life Cycle and Development Process

The product lifecycle is a core process for industrial companies, increasingly viewed holistically to transcend boundaries between phases, departments, and IT solutions. This comprehensive perspective spans from the initial product idea through to its recycling. The product lifecycle encompasses the complete planning and development of products and their associated resources, manufacturing and assembly processes, production, utilization, operation, and recycling [6].

2.2. Product Development Process

Product development is a crucial component within the product lifecycle, encompassing organizational units and processes within a company [7]. The product development process as the systematic set of activities of introducing a new or enhanced product to the market. Product development is information processing that transforms customer requirements and needs into product design and manufacturing information. Despite increasing digitalization, human involvement remains central in product development. The characteristics, experience, knowledge and social competencies of individuals can determine the success of development projects [6], [7]. Digital engineering supports the product development process by employing information technologies [8]. In this scope, GenAI as a novel digital technology should be considered for digital engineering.

2.3. Overview of Deep Generative Models

Generative algorithms in machine learning aim to create new, high-quality samples that are indistinguishable from training data. Specifically, GenAI are algorithms that generate new data samples using deep learning models, such as GANs, VAEs, and Transformers [4]. Despite sharing this common objective, these algorithms vary significantly in their underlying mathematical principles.

2.3.1. Generative Adversarial Networks

Generative Adversarial Networks (GANs), introduced in 2014 by Goodfellow et al. [9], have since become a widely used method for generating new data samples from a given training dataset. A GAN is composed of two components: the generator and the discriminator. The generator maps an arbitrary noise distribution to the target data distribution enabling it to generate new data samples. On the other hand, the discriminator is trained to distinguish between real and generated data from the generator. Both models are typically implemented using feed-forward deep neural networks. As the discriminator's ability to discern real from generated data improves, the generator concurrently enhances its capability to produce data that can deceive the discriminator. Additionally, to steer the generator's output, a condition vector can be injected into the generator and discriminator [10]. For instance, in image generation tasks, the condition vector may encode specific attributes of the desired image, such as the depicted subject.

2.3.2. Variational Autoencoders

Introduced in 2013 by Kingma et al. [11], Variational Autoencoders (VAEs) have demonstrated success across various machine-learning applications. VAEs operate under the assumption that high-dimensional data follows a lower-dimensional, latent distribution that can be learned. The VAE architecture comprises two primary components: the encoder and the decoder. The encoder's role is to determine the mean and variance of the latent distribution given the training data. At the same time, the decoder uses a latent vector, sampled based on the discovered mean and variance, to construct a new high-dimensional data sample. This approach enables VAEs to effectively learn and generate complex data distributions.

2.3.3. Transformers

Transformers [1] have marked a significant advancement in deep learning, particularly in handling sequential data such as text. Their effectiveness lies in their ability to capture long-range dependencies through self-attention mechanisms. This architectural innovation has profoundly impacted generative AI, facilitating the development of models like GPT

(Generative Pre-trained Transformer), which excel in generating coherent and contextually relevant text [12]. Tasks such as text completion, summarization, and creative writing have substantially improved due to transformers' capacity to comprehend and produce sequences embedded with nuanced context. Their versatility across diverse domains and applications underscores their role in expanding the frontier of AI capabilities, particularly in generating human-like text and fostering creativity.

2.3.4. Diffusion Models

Diffusion models represent a potent category of generative models within the field of artificial intelligence, notable for their capability to generate high-fidelity images and data samples. These models operate by sequentially applying a sequence of transformations to an initial distribution, typically a simple Gaussian, progressively refining it to approximate the intricate distribution of real-world data [13]. Unlike conventional VAE or GANs, diffusion models emphasize the gradual enhancement of noise over time rather than direct generation from a latent space. This iterative refinement mechanism enables diffusion models to produce realistic samples imbued with intricate details, rendering them suitable for diverse applications such as image synthesis, text generation, and beyond [14]. The effective modeling of complex data distributions underscores diffusion models' potential as promising instruments in advancing research within generative AI.

3. Methodology

Our research aims to contribute by investigating the usability of GenAI capabilities throughout the PLC and PDP [15]. To this end, we conduct a scoped review [16] of proposed GenAI use cases presented in grey and scholarly literature.

3.1. Academic Literature Review

We systematically conducted a literature review following the methodology outlined by Webster et al. [17] to ensure rigorous scientific inquiry. Our focus was identifying reviews, case studies, and surveys published in English or German from 2021 onwards that explore applications of generative AI in engineering and manufacturing.

Base Keywords		generative ai, generative models, generative artifical intelligence, generative deep-learning, genai
+	Requirements	requirements, specifications
	Planning	planning
	Development	development
	Production	production
	Sales	sales, marketing
	Operations	operations
	Disposal	disposal, recycling
	PDP	product development process
	PLC	product life cycle

Table 1: An overview of the keywords used for the academic literature review.

Specifically, we searched for discussions encompassing generative AI, generative models, generative deep learning, and related terms. Emphasis was placed on papers discussing VAEs, GANs, Transformer-based or diffusion models, and their relevance to the PDP in the manufacturing sector. The base keywords of our inquiry were combined with the stage or process specific keywords and adapted to the search string syntax of the respective database as detailed in table 1. We used the Scopus, Web of Science and IEEE Xplore databases.

3.2. Grey Literature Review

Further, we included grey literature using the methodology outlined by Giustini [18]. Grey literature encompasses documents from governmental, academic, and business sectors protected by intellectual property rights. These materials are of sufficient quality to warrant collection and preservation yet are not under the control of commercial publishers [19]. Grey literature is significant in complementing academic literature search and synthesis, especially when exploring emerging, rapidly evolving, or interdisciplinary topics [20], [21].

Employing a planning grid, we tracked access and saved citation details. Our search targeted white papers, case studies, and industry reports from sources like technology consultancies, AI firms, and industry software vendors.

4. Results

	Hits	Abstract	Full		Hits	Abstract	Full		Hits	Abstract	Full
PLC	5	2	2	PDP	11	3	3	Requirements	28	9	4
								Planning	33	1	1
								Development	14	5	3
								Production	52	9	4
								Sales	6	2	2
								Operation	48	9	6
								Disposal	1	0	0

Table 2: Results of the academic literature review. Darker green correlates with a higher number of papers.

Our nine queries into each of the three academic databases totaled 198 hits, of which 20 were deemed relevant based on consistent criteria to answer our research questions (see Table 1 for details). In grey literature, 180 websites were scanned, of which 17 are relevant. The identified use cases were systematically organized into a concept matrix, resulting in 85 use cases, of which grey literature contributed 70 and academic literature 15. The development, operation, and production stages host most use cases of GenAI. Virtual assistants and content generators are the most frequently used GenAI capabilities, but this is not equally distributed across all stages. Notably, so far, no applications of Generative AI have been proposed for requirements engineering and product disposal.

	Requirements	Planning	Development	Production	Sales	Operation	Disposal	Universal	Σ
Content Generator			7	8	4	2		5	26
Assistant	1	3	8	6	2	9		2	30
Information Retrieval	1	1		3	1	2		2	9
Analytics		2	1	9	1	3		1	17
Σ	2	6	16	26	8	16	0	10	

Figure 2: The resulting 85 applications of GenAI from our literature review arranged along the PLC with the PDP marked green. The life cycle definition is delineated from [6].

Stage	No.	Use-Case	Literature Reference	Survey Rating
Requirements	1	Supporting in the requirements eliciation process	[22]	7.2
	2	Retrieving requirements from unstructued text	[23]	7.8
Planning	3	GenAI models capable of ingesting large amounts of data for planning purposes	[24], [25], [26]	7.8
	4	GenAI's capability to match feature requirements with specifications	[27]	7.7
	5	Creating a project plan using large language models	[28]	7.7
Development	6	Generating novel designs based on prompts early in the development process	[24], [29], [30], [31]	6.3
	7	Quickly improving and optimizing models in terms of weight, cost, manufacturability, or mechanical properties	[24], [26], [32]	7.8
	8	Generating and exploring a wide range of designs for customization or optimization towards different objectives	[33], [34]	7.8
	9	Writing software code for control modules	[35]	7.8
Production	10	Utilizing GenAI to reconcile sensor data with lessons learned from prior outages, thereby detecting anomalies, predicting failures, and identifying areas for improvement.	[24], [26], [32], [36]	7.5
	11	GenAI acting as a supply chain advisor, optimizing logistics, and simulating potential disruptions.	[26], [27], [37]	8.2
	12	In procurement language models can be used to pre-screen supplier bids and assess contracts	[25]	7.4
	13	Generate a training curriculum and videos for educating workers and provide a chatbot for quick access to training material	[27], [38], [39]	8.5
	14	Provides insights into inventory levels and warehouse	[25], [32]	7.6
	15	GenAI's capability to detect faulty produced components	[32]	8.3
Sales	16	Utilizing language models and image generators for creating customized sales content	[24], [39], [40]	8.2
	17	ChatBots' provision of the most relevant data to sales teams	[25], [27]	7.9
	18	Forecasting of demand scenarios	[25]	7.2
	19	Transcription and summarization of sales calls	[41]	8.9
Operation	20	Utilize language models as automated and accelerated customer service agents.	[25], [26], [27], [35], [42]	8.6
	21	With language models training materials for maintenance of the product can be created	[26]	7.2
	22	GenAI's ability to predict product failure occurrences.	[27]	6.5

Table 3: The resulting use cases after deduplication by clustering and including the references to the literature source and the survey result average.

Our analysis first showed that the GenAI capability leveraged in the use cases could be further categorized as content generation, virtual assistance, information retrieval, or analysis. Our literature review identified duplicate use cases of generative AI across multiple publications. We clustered these use cases to gain a comprehensive understanding and eliminate redundancy. This approach enabled us to obtain clear and distinct descriptions of applications currently discussed in the literature. By identifying and clustering these use cases, we highlighted those with the most significant potential for advancing product development.

Finally, using the clustered use cases, we surveyed 19 product development experts on their opinions on the feasibility of each use case on a scale from 1 (“Very unlikely that this use case can be implemented with AI.”) to 10 (“Very likely that AI can solve this use case.”). The results can be found in table 3.

5. Discussion

The overall low volume of relevant academic evidence highlights the novelty of this research domain, indicating the need for further investigation. A possible explanation for this might be the long lead time in academia from the start of a research project to publication. In contrast, grey literature already provides many practical GenAI use cases. Still, the low signal-to-noise ratio, with only one relevant source per approximately ten hits, can be attributed to the current hype surrounding GenAI. Numerous semantically duplicate use cases suggest a need for more structured exploration in this field. The prevalence of use cases in grey literature suggests that academic research needs to catch up with commercial exploration.

5.1. Assistant Use Cases

GenAI Assistants come in the form of chatbots combined with information retrieval to efficiently access extensive knowledge databases. It addresses the persistent challenge of large-scale product development projects that generate thousands of documents, including functional specifications, manuals, and technical documentation [43]. The need to swiftly retrieve such information during operations underscores the significance of streamlining access to technical documentation. Efforts to harness GenAI in this context aim to improve information management and mitigate complexities associated with information retrieval, fostering enhanced productivity and resource utilization. Chatbots must be invoked and instructed by the user when it would be more desirable for assistants to gather information the user might require proactively without the inefficiencies of the chat interface.

5.2. Content Generation Use Cases

Efforts towards rapid generation of tailored digital content are increasingly sought after. Identified use cases highlight diverse media requirements such as natural language, technical sketches, and software code. These applications primarily focus on two pivotal scenarios: creating instructional materials to train personnel in production processes and generating engineering designs during developmental stages. In engineering design tasks, strides have been made with publications detailing the use of GenAI to generate computer-aided design models for technical product development. However, progress is impeded by the need for adequate training datasets essential for refining and enhancing model performance in these complex tasks.

5.3. Information Retrieval Use Cases

Typical information retrieval tasks involve knowledge extraction followed by text summarization; processes often associated with chatbots utilizing information retrieval capabilities. Currently, all identified information retrieval tasks assume data stored in natural language. However, valuable engineering information often resides in technical drawings, 3D models, and other visual formats. Developing a multi-modal information retrieval model thus presents a compelling research avenue to enhance accessibility and usability across diverse data formats in engineering contexts.

5.4. Generative AI for Analytics Use Cases

The use case descriptions in this context often appeared vague and obfuscated, needing clear explanations of how generative algorithms are employed to achieve the desired outcomes. For instance, predictive maintenance is a discriminative machine learning task that involves classifying potential machine failures based on sensor data rather than generating new content [44]. Similarly, sentiment analysis and extracting insights from unstructured data fall under data analysis.

5.5. Survey Results

Our survey results notably indicate low ratings for use cases #6 and #22 in Table 3. Use case #22 pertains to analytics, while use case #6 involves new product design. The low rating for use case #6 may be attributed to the prevailing assumption that GenAI cannot replicate the human creative process. It is perceived that, rather than generating novel ideas, GenAI merely replicates its training data, necessitating human ingenuity for true innovation [45], [46]. While it is observed that the generation of novel content is less diverse, GenAI can still improve the creative process in collaboration with a human operator [47].

5.6. Possible Detriments for Generative AI in Product Development

Examining both success stories and setbacks is crucial for comprehensive research. However, failures are less likely to be publicized compared to positive results, a phenomenon known as publication bias [48]. This bias leads to an overrepresentation of positive findings in the literature, while negative results often need to be reported more. This issue is particularly pronounced in grey literature produced by businesses that prefer to portray themselves as successful [49]. In addition, success might not be a good indicator of exceptional skills or ability but rather a combination of high-risk tolerance and coincidence [50].

Furthermore, the field of GenAI, which gained significant attention with the release of ChatGPT in late 2022, is still in a dynamic phase with many ongoing academic research and industry projects. These projects have yet to be conclusively deemed successes or failures, as long-term results will still be observed and measured.

6. Conclusion and Outlook

This scoped review emphasizes the emerging state of GenAI in the PLC and specifically in digital engineering, validating our initial assertion of its underexplored potential and marking our review as a step towards elucidating the domain. Currently, the understanding of GenAI use cases still needs to be more specific. However, rapid technological advancement and growing research interest require some use cases to be thoroughly elaborated and examined. According to our results, the highest potential for future research is multi-modal information retrieval systems and the generation of technical engineering designs.

Developing a universal framework for evaluating GenAI use cases in digital engineering holds promise in efficiently allocating resources and focusing on impactful initiatives amidst the many discovered applications. Further, it might be insightful to study failed GenAI initiatives in the future. Therefore, our research will continue to explore GenAI as a part of digital engineering in the PDP and PLC.

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