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Evaluating the Current Role of Generative AI in Engineering Development and Design - A Systematic Review

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Abstract: Generative Artificial Intelligence (abbr. GenAI), although still in its early stages, is already beginning to significantly transform various industries as a potentially disruptive technology. This paper presents a comprehensive systematic literature review investigating the applications and capabilities of generative AI with a particular focus on its current role in engineering disciplines and the product development process. By synthesizing perspectives from various disciplines that have incorporated generative AI, this review aims to showcase the latest progress and explore potential future research paths and challenges in applying generative AI to engineering design.

Keywords: Generative Artificial Intelligence, Engineering Design, Product Development, Systematic Literature Review

1 Introduction and Motivation

Generative Artificial Intelligence (GenAI) represents a dynamic and rapidly progressing field, bringing transformative change across multiple domains including the Creative Arts (Anantrasirichai and Bull, 2022), Medicine (Waqas et al., 2023) and Education (Bahroun et al., 2023). Beyond these domains, GenAI is expected to significantly reshape global economies. Latest studies suggest a growing influence on productivity across all industry sectors (Chui et al., 2023).

The recent advancements in GenAI have been propelled by significant breakthroughs in deep learning methods and the growing accessibility of expansive datasets (Bandi et al., 2023). GenAI models leverage deep neural networks to identify patterns and features within large datasets enabling them to generate novel content similar to their training data. This capability spans a range of data types such as text (Brown et al., 2020; Scao et al., 2022; Touvron et al., 2023), images (Ramesh et al., 2022; Rombach et al., 2022; Saharia et al., 2022), audio (Engel et al., 2019; Ren et al., 2020) and even 3D-objects (Nichol et al., 2022). This technology also holds significant potential for the field of engineering, particularly due to its capacity to leverage large amounts of data. As engineering challenges become increasingly complex and data-intensive (Quan et al., 2023; Tikayat Ray et al., 2023), GenAI systems offer a way not only to synthesize and analyze this information effectively but also to generate novel solutions and insights.

Given the surging interest in GenAI, characterized by its rapidly expanding knowledge base and the emergence of new applications and theoretical frameworks, a systematic review becomes indispensable. This analysis seeks to capture the current state of GenAI, highlighting specific challenges in the process. Currently, there is a notable absence of a comprehensive review that examines GenAI, its applications, and the unique challenges it presents within the domain of engineering design. This study begins by collating and condensing essential information about the current state of the art in GenAI to establish a foundational understanding for the systematic literature review that follows.

2 State of the Art of Generative Artificial Intelligence Models

With breakthroughs like ChatGPT (OpenAI, 2022) and DALL-E-2 (Ramesh et al., 2022), GenAI has recently expanded beyond its computer science roots to capture mainstream attention. Building upon conventional AI, which is centred around analysis tasks like classification or regression, GenAI marks a paradigm shift towards creating, characterized by deep learning models that generate novel content based on their training data distribution (Zhang et al., 2023).

A preliminary literature search on GenAI reveals a surging volume of research across multiple domains, with the most prominent findings in Healthcare (Gong et al., 2023; Jadon and Kumar, 2023; Jayakumar et al., 2023; Waqas et al., 2023) and Education (Bahroun et al., 2023; Tan et al., 2023), extending also to domains such as Chemistry (Tang et al., 2021), Financial (Chou and Cho, 2023) and the Metaverse (Qin and Hui, 2023). This distribution aligns with insights from another recent study, which also identified Healthcare and Education as leading areas of focus (Kanbach et al., 2023). Moreover, Kanbach et al. detail the types of GenAI employed, showing a prevalence of text-based applications, with further significant applications in data analysis, image, audio and code generation, reflecting the diverse utility of GenAI.

Fundamentally, GenAI models can be categorized based on their foundational architectures and operational mechanisms (Bandi et al., 2023; Y. C. Wang et al., 2023; Wu et al., 2023) as shown in Figure 1.

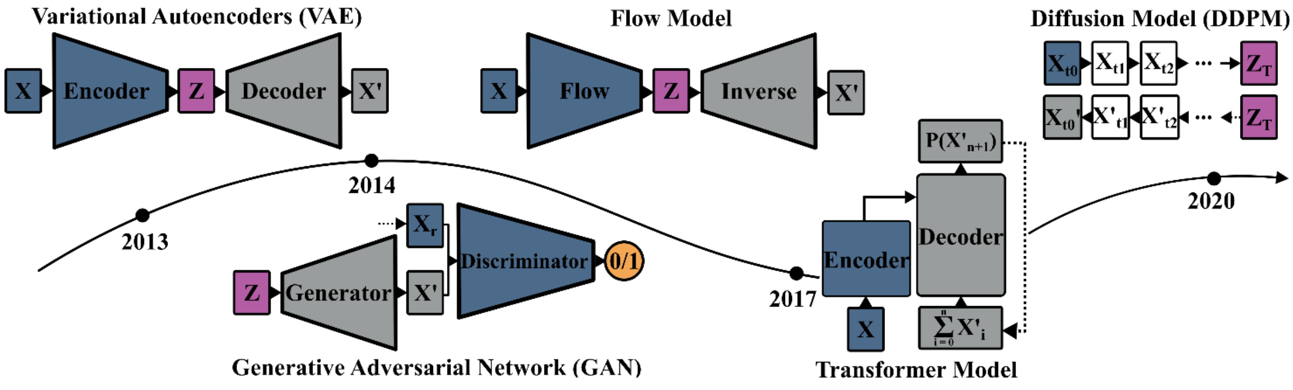

Figure 1: Overview of Key Generative AI Architectures

Variational Autoencoders (VAE), conceptualized by Kingma and Welling (2013), compress input data (X) into a compact latent representation (Z) and then aim to reconstruct X from Z. These models distill essential features into lower dimensions via an encoder, enabling the generation of new samples (X') via a decoder. The training of VAEs involves progressively diminishing the discrepancy between the original input X and its reconstructed counterpart X'.

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2014), feature a generator that uses a latent representation (Z) to produce synthetic data (X') and a discriminator evaluating its authenticity against real data (X_r). This adversarial setup leads to a continuous improvement cycle: the generator strives to create more realistic data, while the discriminator enhances its ability to discern real from synthetic, thereby refining the capabilities of both components.

Flow models, popularized by Dinh et al. (2014), use reversible transformations to map input data (X) to latent representations (Z). Through sampling from Z and applying the inverse transformations new data (X') is generated.

Transformer models, pioneered by Vaswani et al. (2017), use a self-attention mechanism and often employ an encoder-decoder structure. They process input data (X) in the form of tokens, with the encoder passing on information to the decoder. The decoder recursively generates new tokens using the previously generated tokens ($\sum_{i=0}^{n} X_i'$) as inputs. It then selects the next token (X'_{n+1}) based on the highest output probability scores ($P(X'_{n+1})$) across the model's vocabulary.

The Denoising Diffusion Probabilistic Model (DDPM), introduced by Ho et al. (2020), trains a deep neural network for image synthesis. Training involves a forward pass where noise is incrementally added to the initial data (X_{t0}), eventually transforming it into a noise-dominated state, resembling Gaussian noise (Z_T). The backward pass reverses this, predicting and systematically removing noise from Z_T to decode and create new data (X').

Today's GenAI landscape features a wide array of model variations and combinations, with hybrid models blending different techniques and architectures to transcend single-model limitations (Bandi et al., 2023). Beyond architectural distinctions, GenAI models can also be categorized based on input-output functionalities, reflecting their practical applications. The classification shown in Figure 2 is based on the extensive surveys of Gozalo-Brizuela and Garrido-Merchan (2023) and Zhang et al. (2023). It illustrates various output examples alongside popular models employed in these contexts. Furthermore, GenAI models can also be categorized according to modality, distinguishing between unimodal and multimodal types, as discussed by Cao et al. (2023).

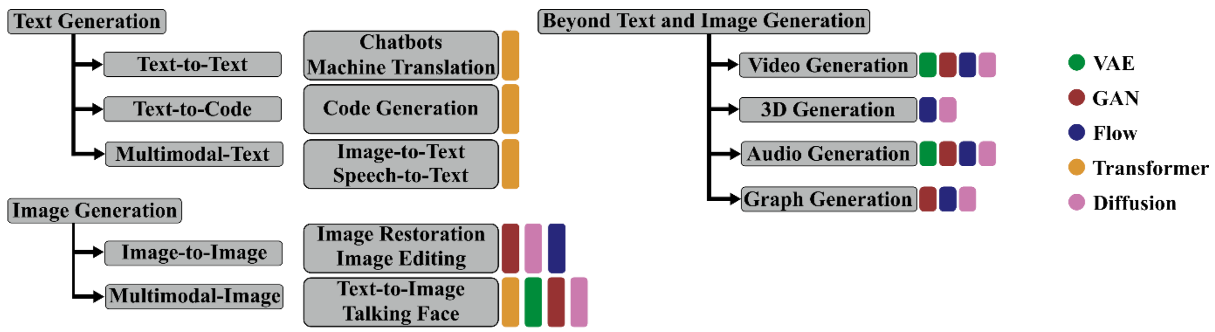

Figure 2: Classification of Generative AI Models by Output Functionality and Modality

3 Research Methodology

This systematic review's methodology is based on the established techniques and recommendations for conducting systematic reviews, as outlined by Kitchenham (2004). The initial step defines the key research questions (RQs), which led to the creation of targeted search strings, enhanced by a keyword extraction algorithm. The literature retrieval process leveraged the resources of the IEEE Xplore, Scopus, and Web of Science (WoS) databases. Following the literature retrieval process, a thorough literature screening phase ensued. During this multi-stage process, the titles, abstracts, and keywords of each source were assessed for their alignment with the defined RQs. Finally, the content analysis phase encompassed a detailed examination and synthesis of the main content from the screened literature.

3.1 Definition of Key Research Questions

To offer an in-depth understanding of the GenAI landscape in engineering this study is structured around two key RQs. These questions strategically shift focus from a general perspective of GenAI's capabilities and limitations across diverse engineering domains to a more detailed examination of its current use in the product development process (PDP). The research questions are as follows:

RQ1: How is generative AI currently being utilized in various engineering disciplines?

RQ2: What are the current applications, challenges, and future potentials of generative AI in the PDP?

3.2 Search String Definition

To ensure a thorough review amid the exponential growth of scientific publications (Bornmann and Mutz, 2015) it is crucial to capture the full spectrum of terminology used in the targeted field. To achieve this, preliminary databases of relevant literature were established in parallel with defining the RQs. Subsequently, a python keyword extraction algorithm utilizing the Natural Language Toolkit libraries (Bird et al., 2009), was used to extract arrays of keywords from the initial databases. The keyword extraction focused on unigrams and bigrams, removing common stop words, and employing word lemmatization. For each RQ, the most frequent keywords were used to supplement the creation of targeted search strings, structured in three blocks: the first defines general GenAI-related terms, the second delves into more specific types of generative outputs while the third focuses on the scope relevant to the RQ. While multiple databases were utilized, the search strings detailed below are specific to Scopus. In adapting for different databases, the syntax was adjusted to match the indexing conventions of IEEE and WoS. For IEEE, “Document Title” was used instead of “TITLE”, and for WoS “ALL” and for IEEE “All Metadata” was used instead of “TITLE-ABS-KEY”.

RQ1: *TITLE* (("Generative AI" OR "Generative Artificial Intelligence" OR "AI Generated Content" OR "GAI" OR "GenAI" OR "Gen AI" OR "Gen-AI" OR "Artificial Intelligence Generated Content" OR "AIGC") AND ("Engineering" OR "Industry" OR "Application*" OR "use" OR "for"))
AND *TITLE-ABS-KEY*
((("Language" OR "Natural Language" OR "NLP" OR "Unimodal" OR "Multimodal") AND ("Model*" OR "Generation")) OR (("Text" OR "Image" OR "Picture" OR "Audio" OR "Video" OR "Knowledge" OR "Content" OR "Code") AND "Generation") OR "Training" OR "Learning" OR "Data" OR "Machine Learning" OR "Neural Network*" OR "Generative Algorithm*" OR "Large Language Model*" OR "LLM")
AND
(Engineering AND ("Mechanical" OR "Automotive" OR "Aerospace" OR "Manufacturing" OR "Materials" OR "Electrical" OR "Electronic" OR "Computer" OR "Software" OR "Chemical" OR "Environmental" OR "Civil" OR "Structural" OR "Architectural" OR "Transportation" OR "Systems" OR "Mechatronics" OR "Industrial" OR "Biomedical" OR "Medical" OR "Biological" OR "Marine" OR "Nuclear" OR "Agricultural"))
AND *NOT TITLE* (("Education"))

RQ2: *TITLE-ABS-KEY* (("Generative AI" OR "Generative Artificial Intelligence" OR "AI Generated Content" OR "GAI" OR "GenAI" OR "Gen AI" OR "Gen-AI" OR "Artificial Intelligence Generated Content" OR "AIGC" OR "Large Language Model*" OR "LLM" OR "Generative Algorithm*")
AND
((("Language" OR "Natural language" OR "NLP" OR "Unimodal" OR "Multimodal") AND ("Model*" OR "Generation")) OR (("Text" OR "Image" OR "Picture" OR "Audio" OR "Video" OR "Knowledge" OR "Content" OR "Code") AND "Generation") OR "Training" OR "Learning" OR "Data" OR "Machine Learning" OR "Neural Network*" OR "Generative Algorithm*" OR "Large Language Model*" OR "LLM")
AND
("Product Design" OR "Process Design" OR "System Design" OR "Machine Design" OR "Engineering Design" OR "Tool Design" OR "Component Design" OR "Assembly Design" OR "Manufacturing Design" OR "Production Design" OR "Design Methodology" OR "Product Development" OR "Development Stage"))
AND (*LIMIT-TO* (*SUBJAREA* , "ENGI")

3.3 Reduction Methodology

For the literature retrieval process, the "advanced search" feature of Scopus, IEEE, and WoS was used to explore all indexed publications in English language which returned 121 results. The literature screening phase implemented a multi-stage filtering process as illustrated in Figure 3. This process included the removal of duplicate studies in Level 2, followed by an assessment in Levels 3 and 4 to determine the relevance of the retrieved literature to the RQs. After these stages, a total of 30 papers were identified as relevant and selected for further in-depth analysis. In the final stage, the snowballing method was used to examine references cited in analyzed papers, aiming to uncover any additional relevant literature not captured in the initial search, thereby enhancing the literature review's comprehensiveness.

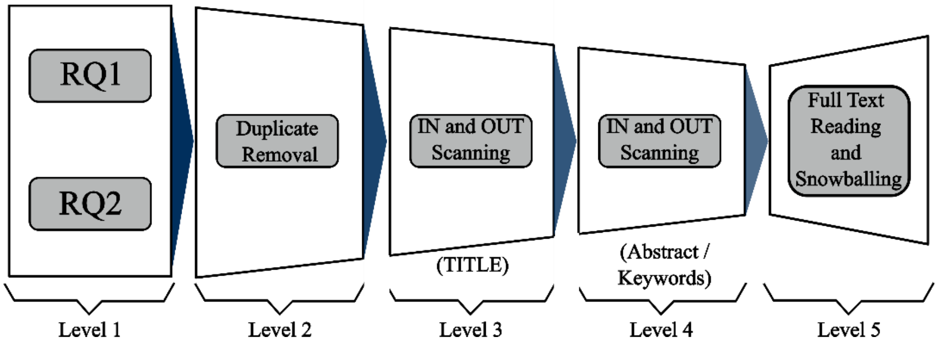

Figure 3: Visualization of Multi-Stage Reduction Methodology

4 Results and Analysis of Resulting Literature

The reduction methodology yielded 102 papers post-Level 2, which were then screened by the authors. This screening process, detailing the number of results identified for each RQ at different levels, is depicted in Figure 4.

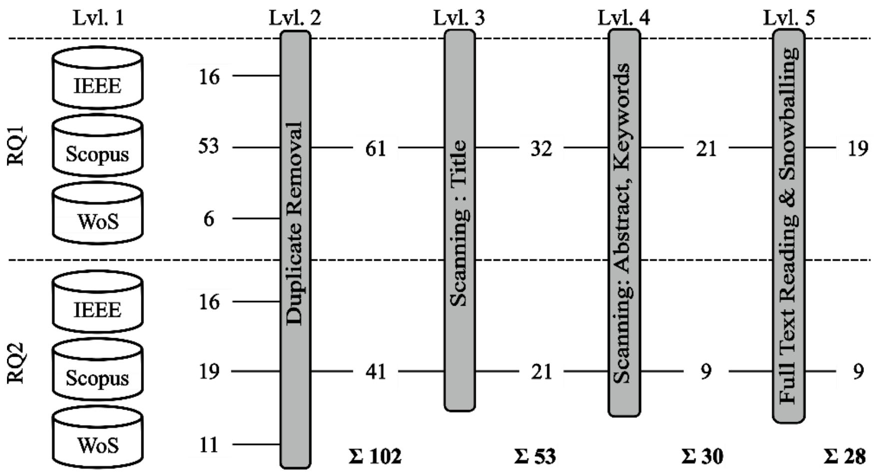

Figure 4: Visualization of Resulting Literature

The research initially focused on the engineering disciplines in RQ1, where the goal was to understand the integration of GenAI in this field. This search uncovered 19 relevant results spread across multiple engineering domains. Moving to RQ2, the exploration delved into the specific applications of GenAI in the PDP. Despite broadening the search criteria using '*TITLE-ABS-KEY*' for all terms, only 9 relevant papers were identified, highlighting the relatively uncharted territory of GenAI in this specific domain. These findings underline that while GenAI is evolving, its adoption in engineering and product development is in early stages, offering considerable scope for future research and innovation.

4.1 Analysis of RQ1 – GenAI in Engineering Disciplines

The utilization of GenAI across various engineering fields unveils a broad spectrum of applications, each marked by distinct impacts and challenges, as well as overlapping themes. In addressing RQ1, the relevant literature was systematically organized by domain, highlighting specific challenges and applications relevant to each field. The following analysis is structured to offer insights into the following domains: Biotechnology and Medical Engineering (4), Chemical Engineering (2), Civil Engineering (2), Computing/Software Engineering (5), Materials Science (1), Extended Reality (2), Synthetic Data Generation (2) and Industrial Engineering (1), with the numbers in parentheses indicating the volume of relevant literature found in each domain.

GenAI has shown promise in **Biotechnology and Medical Engineering**. For instance, VAE, GAN, flow and diffusion models have been employed for brain image computing (Gong et al., 2023) spanning numerous tasks including cross-modality image synthesis and graph-based brain network analysis. Multimodal GenAI methodologies have also been applied to optimize emergency department care by producing draft radiology reports from input images (Huang et al., 2023; Minutti-Martinez et al., 2023). In synthetic biology, GPT-4 has been leveraged for knowledge mining (Xiao et al., 2023) underscoring the potential of LLMs in streamlining data extraction and assisting in labour-intensive workflows. Despite many applications, multiple challenges arise such as the small sample or high dimensional data problem, measuring the overall accuracy of generated outputs, model interpretability and human oversight in AI-assisted clinical care.

In **Chemical Engineering**, the use of GenAI is significantly transforming the landscape of drug discovery. One of the foremost challenges in this field has been the efficient identification of viable drug candidates from extensive molecular libraries, of which only a small fraction are synthesizable (Tang et al., 2021). Addressing this challenge, a study by Grisoni et al. (2021) has demonstrated the efficacy of GenAI using an optimized chemical language model designed for novel molecule creation. Their model has been notably successful in generating unique and chemically valid molecular structures, with 55% not found in existing databases. Further illustrating this transformation, Insilico Medicine utilized GenAI in each stage of the preclinical drug discovery process which typically incurs costs of over $400 million and spans up to six years but accomplished the same objectives in just one-third of the time and at one-tenth of the cost (Yao, 2023).

In the **Civil Engineering** sector, GenAI, particularly through the use of GANs, Graph Neural Networks (GNNs), and VAEs, has been utilized in building structure design (Liao et al., 2024) and the design of engineered cementitious composites (Yu et al., 2023). Despite efficiency, sustainability and creativity enhancements, challenges persist, such as limited high-quality training data availability, difficulty of extracting data from heterogenous sources and developing models that grasp the complex relations between design parameters as well as mechanical and economic constraints.

In **Computing and Software Engineering**, GenAI is catalysing advancements across diverse applications. The auto-generation of high-quality SQL statements is enhancing the efficiency and accuracy of database query formulation (Troy et al., 2023) while GAN and Transformer Language Models are advancing cyber threat-hunting by combining data analysis with automatic report generation (Ferrag et al., 2023). In software engineering LLMs offer support to developers for reengineering software variants into Software Product Lines (Acher and Martinez, 2023). Additionally, in the development of interactive systems, GenAI expedites various stages of the lifecycle, from ideation to testing, by generating rapid prototypes and solutions (Schmidt, 2023). Moreover, synergies between generative AI and quantum computing have been explored for their potential to revolutionize data generation, simulation and optimization processes (Pise et al., 2023). Technical challenges faced include scalability issues regarding latency, memory, cost and high computation requirements. Furthermore, energy consumption, privacy, execution consistency and data quality issues in LLMs are discussed.

GenAI shows promise in **Materials Science** for knowledge extraction and computational support, however challenges such as the need for high-quality data and domain knowledge, and limitations in generalization ability, interpretability, as well as limited mathematical understanding highlight areas that require further research and development (Liu et al., 2023).

In the domain of **Extended Reality**, GenAI has been used to enhance multimedia content creation with LLMs and text-to-image models (Y. Hu et al., 2023) and to generate conditioned traffic and driving data for autonomous driving simulations in vehicular mixed reality scenes (Xu et al., 2023). In augmented reality content generation, challenges like the need for real-time interaction and addressing privacy in multi-user settings are identified as future improvements. For autonomous driving, results show that while synthesized datasets generally enhance model performance, the degree of improvement varies based on the specific characteristics of the datasets generated.

In the realm of **Synthetic Data Creation**, GenAI is proving to be a useful tool, particularly in industrial applications and healthcare. Faced with the scarcity and privacy concerns of industrial datasets, researchers have turned to GenAI models to create synthetic data. This approach is exemplified in a study focusing on generating datasets for products like bolts and screws, using stable diffusion techniques (Sasiaowapak et al., 2023). Additionally, in healthcare, GenAI has been used to address issues such as insufficient data, data imbalance, and biases in training samples (Lan et al., 2023).

In the domain of **Industrial Engineering** and more specifically operations and supply chain management, a study by Fosso Wamba et al. (2023) highlights that the adoption of GenAI technologies significantly enhances overall supply chain performance. A key finding is that organizations that have implemented GenAI, such as LLMs, perceive considerable benefits post-implementation, including increased efficiency. However, certain challenges such as ensuring the consistent quality of responses and the handling of confidential information remain.

The overall use of GenAI across diverse engineering fields highlights its transformative impact on efficiency and creativity, despite varied challenges and uses. GenAI's widespread application demonstrates its adaptability and versatility to domain specific problems. A consistent theme across these domains is the need for ongoing research to address challenges such as data quality, output accuracy, privacy, and model interpretability.

4.2 Analysis of RQ2 – GenAI in the Product Development Process

The literature search, concentrating on the PDP, yielded nine relevant results. These results, although limited in number, demonstrate an array of GenAI applications across various stages of the PDP such as requirements engineering (1), product design (3), manufacturing design (1), documentation (1) as well as overarching themes such as design knowledge management (1) and the development of human-robot interaction systems (2).

Tikayat Ray et al. (2023) explore an innovative approach to engineering requirements standardization using LLMs in the context of Model-Based Systems Engineering (MBSE). The primary use case is to address the complexities and ambiguities often found in natural language (NL) engineering requirements. These requirements, fundamental to system design and development, typically lack structure for direct translation into MBSE models. The authors build upon recent developments in NL-processing using a combination of LLMs, particularly fine-tuned versions of Bidirectional Encoder Representations from Transformers (BERT), to convert NL requirements into machine-readable formats. The paper outlines a two-fold strategy whereby the first step involves creating a requirements table from free-form NL requirements, and the second step involves identifying templates for requirements based on linguistic patterns in order to be used by less experienced engineers. One of the main issues encountered was the lack of specialized knowledge in LLMs for domain-specific texts prevalent in engineering. This necessitates the fine-tuning of pre-trained LLMs on domain specific corpora improving their performance in these contexts. The authors propose further exploring the potential of LLMs, such as T5 and the GPT family, for rewriting NL requirements, stating that these models could be trained on datasets comprising of NL requirements and their corresponding versions rewritten to conform to industry standards. This would enable the LLM to generate well-structured and standard-compliant requirements from original NL inputs.

There is a small set of studies concentrating on using GenAI in the product design phase. Among these studies, a notable work by Quan et al. (2023) examines the applications of multi-modal AI-generated data to spark creativity in the design process. Another study in this field investigates the deployment of LLMs for providing valuable life cycle assessment (LCA) data, particularly for non-traditional construction materials (Haskara, 2023). Lastly, there's a study by Buehler (2023) that proposes two unique language models. Firstly, MeLM a multi-modal language model for assisting designers in the exploration and analysis of materials for solving forward and inverse mechanics problems. Secondly MechGPT, a fine-tuned LLM that combines diverse general knowledge with domain specific information effectively increasing its capabilities of relating, combining and integrating domain specific knowledge with the general performance of a pre-trained LLM. Analysing and collating information from the aforementioned studies the current use cases for GenAI in product design can be summarized as follows: LLMs, GANs and diffusion models can be implemented to automate the generation of preliminary product schemes or utilize text-to-image synthesis for generating initial product images (Quan et al., 2023). Furthermore, LLMs can be used as text-to-LCA tools for assessing material sustainability in design and construction projects. By analysing materials' specifications and text descriptions against sustainability standards, LLMs can identify unsustainable materials. Additionally, by examining information about materials’ composition, production, and lifespan, LLMs can suggest more sustainable options like recyclable or biodegradable materials, thereby aiding sustainable design efforts (Haskara, 2023). LLM tasks can also be extended to solve abstract problems such as calculating material properties or generating new designs of microstructures (Buehler, 2023). This however raises the challenge of additional pre-processing steps such as encoding the input data into natural language representations. Further challenges include the necessary development of high-quality datasets for fine-tuning domain specific LLMs as MechGPT was trained on mechanics-related Wikipedia articles and is thereby limited to more general mechanics and materials concepts. Moreover, although the study on using LLMs in the LCA has shown opportunities in contributing to more sustainable product design, future research will need to explore the possibilities of integrating these tools into computational design software to effectively assist in the product design process. And although the possibilities of text-to-image synthesis are discussed (Quan et al., 2023) there is limited research highlighting the practical application in the engineering domain.

The use of LLMs in manufacturing design is discussed by X. Wang et al. (2023) where the authors compare LLMs with established knowledge-based systems and promote a technology development roadmap to successfully integrate LLMs in the manufacturing industry. They highlight the potentials of ChatGPT in enhancing human-machine collaboration, knowledge management of multi-modal data across various engineering domains, assisting designers in re-framing design problems through direct feedback and supporting engineering training and education. Despite the potential benefits multiple limitations and challenges are identified. Key issues encompass the reliability of generated content due to limited design and manufacturing knowledge in training datasets, the model's inadequacy in advanced analytical tasks due to limited logical reasoning, and the necessity for user skill development.

A further application of LLMs in the documentation and utilization of assembly process information is discussed by Z. Hu et al. (2023). The authors present a question-answering system for the assembly process of wind turbines, integrating multi-modal knowledge graphs (MMKG) with LLMs. This system addresses the challenge of effectively utilizing multisource heterogenous data and historical assembly process knowledge which assists workers in completing assembly tasks more effectively by providing answers in natural language. The general capabilities of the LLM are supplemented through the combination of knowledge graphs and fine-tuning on domain specific data The authors highlight the practical benefits of combining MMKG with LLMs and point to further research directions such as exploring techniques for processing more complex data and LLM enabled strategies to automatically update and maintain knowledge graphs.

X. Hu et al. (2023) discuss the opportunities of LLMs, specifically ChatGPT, for design knowledge management. Product development as a knowledge-intensive process requires a broad range of knowledge to be shared across multidisciplinary teams (Liu and Lu, 2020; Zhong et al., 2022). Therefore knowledge management can play a pivotal role in successful decision making. The authors state that LLMs have the potential to enable more efficient design processes by serving as a centralized knowledge platform, enabling dynamic, context-aware interactions and collaborative knowledge sharing among diverse stakeholders. Despite potential benefits, multiple limitations and challenges are identified such as the prevalence of bias in LLMs as well as the difficulty of ensuring the accuracy and reliability of the generated output. Additionally, transparency and privacy concerns using closed-source models and the somewhat unexplainable nature of GenAI-Models due to the obscure dependencies between inputs and outputs are raised.

The final two papers explore the potential role of GenAI in the development of human-robot interaction systems. The first proposes a voice-controlled motion-copying system using LLMs to facilitate more nuanced and effective communication between skilled workers and robots (Tanaka and Katsura, 2023). The second discusses the impact of ChatGPT on trust in human-robot assembly tasks (Ye et al., 2023). Both studies demonstrate the effective use of LLMs in enhancing human-robot collaboration, offering users a way to intuitively interact with and control a robot, leading to improved task performance and trust. While users typically experienced reduced mental demand, challenges arose in the system's handling of misunderstandings, leading to problematic decisions. Additionally, the reliance on a unimodal input/output format was found to be a significant limitation in real-world applications. This format often fell short in effectively conveying complex details of the work environment, such as the precise locations of objects.

5 Key Findings

The analysis of the literature corresponding to the two RQs yields several general findings. Firstly, there's an evident contrast in the adoption rates of GenAI across various sectors. While domains like healthcare and education have seen rapid and widespread integration of GenAI, its application in engineering is more gradual and nuanced, as indicated by the findings of RQ1. This trend is observed across a diverse range of engineering disciplines, including chemical, civil, materials science, and industrial engineering, showcasing GenAI's versatility and adaptability. Regarding RQ2, current research predominantly centres around the application of LLMs within the PDP, reflecting the growing interest in harnessing their capabilities for various stages of product design, from ideation to realization. Although the use of GANs and diffusion models is noted, these applications appear less frequent. Likely due to wider accessibility of LLMs combined with the less mature technology of image generators for engineering-specific challenges. This trend suggests an evolving landscape where LLMs will become increasingly integral to the PDP, opening new avenues for innovation. The accompanying diagram provides a structured visual guide, outlining ten key findings in using GenAI for engineering design, as identified in the systematic review.

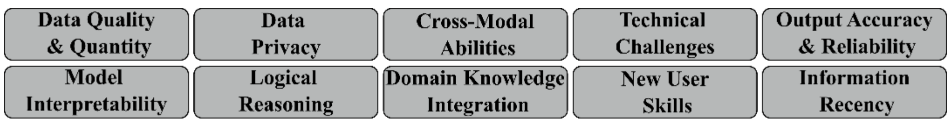

Figure 5: Key Findings for using Generative AI in Engineering Design

(1) Data Quality and Quantity: The acquisition of high-quality, extensive data sets are vital for the effective training of GenAI models across all fields. In engineering, particularly within the PDP, this issue is compounded by the scarcity of comprehensive datasets. Despite this, GenAI also presents the unique opportunity to generate synthetic data, which could bridge gaps in existing data and supplement the training process.

(2) Data Privacy: Data privacy is critically important in engineering when handling proprietary designs and other classified information. However, a significant challenge arises in the development of GenAI models, as they are primarily developed by large companies with extensive financial and computational resources, often as closed-source software which presents substantial barriers to managing data flows and safeguarding privacy effectively.

(3) Cross-Modal Abilities: Engineering challenges are multifaceted, encompassing a variety of formats ranging from textual documentation, technical drawings to 3D models and product images. Addressing these challenges necessitates a tailored approach, where an appropriate combination of GenAI models – such as GANs, diffusion models, or LLMs – is selected based on the specific problem requirements.

(4) Technical Challenges: When training and deploying GenAI models for engineering applications, several technical challenges emerge, including the substantial computational power and associated costs required for training, along with the increased output dimensions compared to conventional AI. This often results in higher latency and demands more robust infrastructure to ensure reliability, posing significant obstacles for the development and scaling of GenAI systems in specific engineering contexts. There is currently a shift towards adapting existing pre-trained models for specific use cases rather than training GenAI models from scratch.

(5) Output Accuracy & Reliability: In engineering's PDP, the accuracy and reliability of outputs is crucial. Accuracy ensures that the model's results are practical and applicable, while reliability refers to the model consistently generating similar outputs for the same inputs. Balancing GenAI's innovative creative capabilities with the need for predictable, repeatable results is essential in meeting the strict standards of the engineering field. Furthermore, GenAI systems reflect biases in their training data which can also negatively affect outputs.

(6) Model Interpretability: Despite the capabilities of generating impressive results, the inherent difficulty in comprehending a model's decision-making process remains a significant concern. This becomes problematic when the model produces undesired outputs, as the lack of interpretability hinders the ability to exert control over the generated results. This can be of particular concern in engineering processes when dealing with safety critical elements, standards, and legal matters. Furthermore, the traceability of decisions may be clouded using GenAI.

(7) Logical Reasoning: A critical challenge in applying GenAI, particularly LLMs, to complex engineering tasks lies in the task of logical reasoning. Currently, these models may lack the advanced logical reasoning capabilities required to solve intricate engineering problems effectively. However, especially in the realm of LLMs there is potential for improvement in this area through advanced techniques like chain of thought prompting.

(8) Domain Knowledge Integration: A recurring theme in leveraging GenAI within engineering disciplines, particularly in the context of the PDP, is the necessity of fine-tuning existing GenAI models with domain-specific data. This approach ensures that the models are not only technically proficient but also deeply aligned with the unique requirements and boundary conditions of engineering product development.

(9) New User Skills: Effective GenAI applications require engineers to interact with advanced systems, interpret model outputs accurately and integrate these insights into the engineering process, while also providing relevant feedback to improve model performance. This approach will inevitably shift engineering work dynamics while an emphasis should be put on complementing existing skills and adherence to a human-in-the-loop approach.

(10) Information Recency: In engineering development projects, it's crucial to maintain the recency of information within GenAI models. This involves regularly updating and retraining the models with the latest data, ensuring that they remain relevant and effective in providing current and accurate insights.

6 Conclusion and Outlook

This systematic review provides a comprehensive overview of the current state and potential of GenAI in the context of engineering development and design. Our findings highlight a varying adoption rate of GenAI across different domains, with many use cases in healthcare and education but a more gradual incorporation in engineering disciplines. The review identifies ten key findings for using GenAI Systems in engineering development and design, encompassing challenges and opportunities with respects to data quality, privacy, cross-modal capabilities, technical challenges, output accuracy, model interpretability, logical reasoning, domain knowledge integration, development of new user skills, and maintaining information recency. Our analysis also shows that LLMs are becoming central in current research, especially within the PDP indicating a shift towards their increased importance in engineering innovation.

These findings underscore the multifaceted impact of GenAI on engineering, highlighting both its transformative potential and the complexities it introduces. Future research will focus on practical LLM implementation in various stages of the PDP whereby the exploration of use cases will be enriched by expert interviews and collaborations with industry partners.

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