

Generative AI and Large Language Models in Engineering and Management: Opportunities and Challenges

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Abstract

The fast pace of Generative Artificial Intelligence (Gen AI) and Large Language Models (LLMs) has brought unparalleled opportunities in engineering and management fields. Nevertheless, although these technologies are popularly debated, there is no coherent scholarly critique on their real world applicability, limitations, and future possibilities. This review paper seeks to fill that gap by exploring systematically the potential, applications, and limitations of Gen AI and LLMs in engineering and management areas. Based on a systematic literature review, the paper examines applications like AI based design, predictive maintenance, strategic planning, and smart automation. It also critically analyzes risks like data bias, computational power, ethical issues, and governance challenges. Through comparative evaluation and selected case research, the research suggests implementable frameworks for ethical adoption, deployability with sustainability, and efficient human AI collaboration. This article contributes to existing scholarly debates through the identification of research directions as well as providing advice for guiding responsible use of Gen AI technologies in engineering and managerial applications.

Keywords: Generative Artificial Intelligence, Large Language Models, Engineering, Management

1. Introduction

A Background and Context

Generative Artificial Intelligence (Gen AI) and Large Language Models (LLMs) signify a major paradigm shift in the area of intelligent computing. These models, established on neural network and deep learning architectures, can produce human like content text, images, code, and even design prototypes on the basis of massive training data [1,2]. Innovations such as Open AI's GPT series [3,4], Google's BERT [5], and Meta's LLaMA [6] have expanded the potential of AI beyond routine automation, enabling context aware reasoning, content generation, and strategic decision support. These capabilities are increasingly being adopted in engineering and management domains where data complexity, rapid decision making, and innovation are essential [7].

B Evolution of AI in Engineering and Management

In the past, AI in engineering was applied to rule based automation, fault detection, and predictive maintenance [5], whereas in management, AI enabled operations research, forecasting, and data analytics [8]. With time, the move toward generative models and natural language processing opened up new possibilities like AI aided design, digital twins, and intelligent enterprise management systems [9]. LLMs, through augmenting human machine interaction, have played a



pivotal role in making adaptive learning systems, strategic simulations, and AI facilitated planning tools work across both domains.

C Research Motivation and Significance

In addition to the observable benefits, GenAI and LLMs' implementation is laden with challenges ebb from ethical issues, algorithmic bias, and explainability, to infrastructural limitations and readiness of the workforce [10,11]. Previous research has addressed technical aspects or single use cases without a holistic interdisciplinary synthesis. This deficiency highlights the requirement for a review based study integrating existing knowledge, assessing real world applications, and marking essential concerns for future research.

D Study Objectives

This paper seeks to cover the following objectives:

1. Critically analyze the implications of Generative AI and LLMs on management and engineering practices.
2. Synthesize the possibilities facilitated by GenAI, for example, intelligent automation, predictive analytics, and human AI collaboration.
3. Enumerate implementation challenges such as ethical, technical, and socio organizational hurdles.
4. To suggest actionable recommendations and areas of future research for ethical and sustainable adoption.

2. Literature Review

A Evolution of AI over Time and Development of Generative Models

AI began in the mid20th century through symbolic logic systems, followed by Machine Learning (ML) that facilitated data driven pattern discovery [12]. The explosion of deep learning in the 2010s spurred dramatic progress in image perception, speech processing, and natural language processing [13]. Generative AI came into being through architectures like variational auto encoders [14] and Generative Adversarial Networks [1], which enabled AI to generate new outputs rather than just scan and process available data. This culminated in the creation of LLMstransformer models that can comprehend and produce sophisticated, contextually relevant text [2], thereby redefining the capabilities and scope of AI.

B Current Progress in LLM Architecture

LLMs have advanced at a breakneck speed with milestones in natural language understanding, reasoning, and contextual generation as follows: BERT (2018, Google) that proposed bidirectional training that enhanced contextual language understanding [5]. GPT series (2018–2023, OpenAI) that is from GPT1 to GPT4, these models showed exponential growth in scale, reasoning strength, and generalization of tasks [3,4]. LLaMA (2023–present, Meta) which focused on maximizing performance without losing ease of use with lightweight architecture [6]. These models have become the pillars for creating applications for real time decision making, smart document processing, and knowledge based automation in engineering and management environments [7].

C Engineering and Management Application Landscape

Generative AI (GenAI) and Large Language Models (LLMs) play a significant role in enhancing various aspects of engineering and manufacturing processes. In design and simulation, they support AI based CAD software and structural simulations, thereby improving the effectiveness

and efficiency of design cycles [15]. In the area of predictive maintenance, these technologies enable condition based maintenance systems that utilize sensor data and AI algorithms to minimize operational costs and equipment downtime [5]. Additionally, in robotics and automation, AI facilitates real time management of robotic operations across manufacturing, quality assurance, and logistics, contributing to higher productivity and precision [16].

Artificial Intelligence (AI) and Large Language Models (LLMs) are increasingly transforming organizational functions across multiple domains. In decision support, AI integrates information from diverse sources to assist in both operational and financial decision making, thereby strengthening strategic planning and execution [8]. For customer engagement, LLMs power intelligent chat bots and personalized communication systems that enhance customer experience and satisfaction [17]. Moreover, in supply chain optimization, AI employs adaptive algorithms to forecast demand, manage inventory efficiently, and streamline logistics operations, resulting in improved responsiveness and cost effectiveness [18].

D Comparative Evaluation: Traditional AI vs. Generative AI

Generative AI models represent a leap forward in flexibility and creativity, making them better suited for dynamic and interdisciplinary fields like engineering and management where contextual awareness and adaptability are crucial [7,9]. (Illustrated in Table 1)

Table 1: Comparison of Traditional AI vs. Generative AI

Feature	Traditional AI	Generative AI
Learning Paradigm	Supervised/RL	Self supervised/unsupervised
Primary Function	Prediction, classification	Content generation, simulation
Flexibility	Narrow task	General purpose, adaptive
Example Models	Decision Trees, SVMs	GPT, BERT, DALL•E
Use Cases	Data analytics, control systems	Text/image/code generation, creative automation

3. Applications of Generative AI in Engineering and Management

A Engineering Applications

AI Driven Design and Prototyping- Generative AI transformed engineering design by allowing quick ideation and optimization of intricate structures. AI driven software like Autodesk Fusion 360 applies generative design techniques to present several optimized designs within specified constraints, making operations more efficient in aerospace, automotive, and architecture fields [15]. They dramatically shorten the development period and expenses by keeping manual design iterations low [16]. Automation in Software Development and Embedded Systems- Generative AI is also speeding up software development with the likes of Git Hub Copilot and Open AI Codex, which help auto complete code, debug, and document [3]. Not only does this enhance speed of development but also software quality. Generative AI models in embedded systems can create firmware code, test automatically, and optimize hardware software co design, resulting in faster time to market [7].

AI driven predictive maintenance lowers downtime by predicting equipment failure based on real time information from IoT sensors [5]. This technique, applied extensively in manufacturing, aerospace, and smart infrastructure, reduces maintenance expenses and enhances operational dependability [8]. Digital Twins and AI Based Simulations- Digital twins, powered by generative AI, mimic physical systems in the digital world, enabling engineers to try out several configurations and simulate results without physical prototypes [9]. Such simulations play a

central role in applications such as smart grid management, city planning, and industrial optimization [18].

B Applications in Management

AI in Strategic Decision Making- Generative AI facilitates strategic decision making by analyzing huge datasets and modeling business environments. Decision systems powered by AI provide insights into risk management, resource allocation, and competitive strategies [17]. Managers can analyze multiple what if scenarios using LLMs to make sound decisions [12]. AI Driven Market Analysis and Forecasting- AI models are able to interpret market trends, consumer behavior, and economic indicators to deliver predictive information. LLMs mimic demand projections, competitor reports, and recommend marketing strategies suited to target audiences [5]. This level of analysis is essential for competitiveness in a turbulent market [8]. AI improves HR functions by automating hiring, performance appraisals, and employee sentiment detection. In finance, predictive analytics and AI powered chat bots simplify financial planning and fraud identification [7]. In supply chain management, generative AI improves inventory, logistics, and demand planning, enhancing resilience and lowering operational expenses [18]. Personalized Customer Experience and Marketing Insights- Generative AI offers hyper personalized customer experiences in the form of chat bots, recommendation systems, and sentiment analysis solutions [10]. Firms are aided by AI authored marketing material, adaptive campaigns, and customer preference forecasting, all of which result in heightened customer engagement and brand advocacy [3]. (Illustrated in Figure 1)

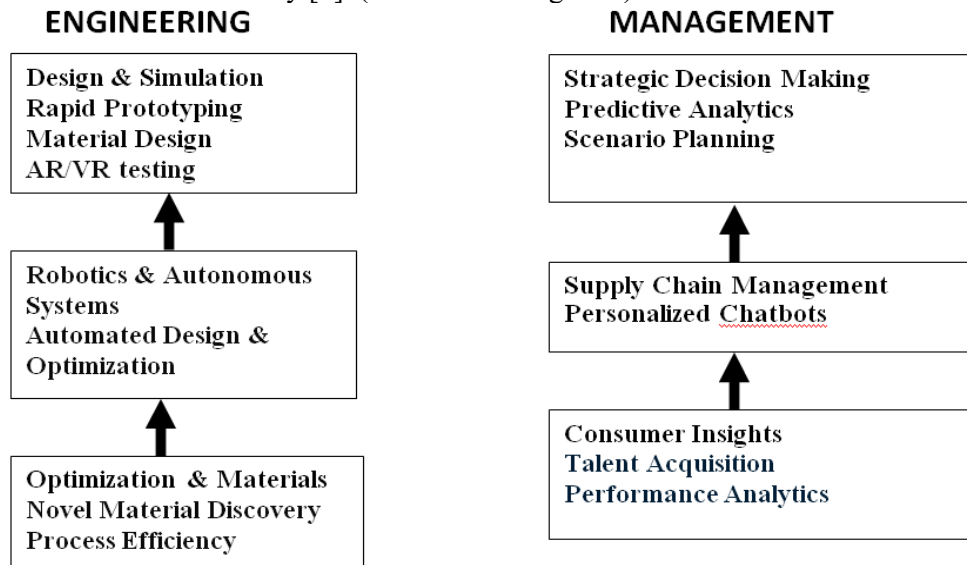


Figure 1: Applications of Generative AI in Engineering and Management

4. Challenges and Ethical Considerations

Generative AI poses various challenges, especially in areas such as engineering and management, where accuracy, trustworthiness, and accountability are paramount. (Illustrated in Figure 2)

A Data Privacy and Security

Generative AI models, in large part, depend on massive amounts of data, often from users or proprietary systems. Use of the data for any and all purposes can create severe privacy issues, particularly when it is personally identifiable or sensitive organizational data [8,3]. For sectors such as healthcare, finance, and defense, protecting this data is essential, as data breaches or illicit use can result in reputation loss and legal ramifications [13].

B Fairness and Bias in AI Outputs

Generative AI systems can inadvertently replicate or magnify social biases inherent in training datasets. For example, hiring algorithm or financial model biases can perpetuate existing discrimination [4,7]. This is particularly problematic in management use cases like HR analytics or performance appraisals, where fairness and impartiality are paramount [18]. Ethical development of AI demands extensive testing, auditing, and utilizing diverse, representative datasets [10].

C Intellectual Property and Plagiarism

Generative models also have the ability to produce content that is virtually indistinguishable from existing material, which poses issues concerning authorship and copyright. In engineering, patented products can be infringed upon by AI generated designs, and in academic circles, there are issues with AI generated content being passed off as original human work [8,6]. Organizations and firms need to establish frameworks for distinguishing between human and AI created work, particularly in research, content creation, and product design [14].

D Transparency and Explainability

Most Generative AI models, especially deep learning based LLMs, are black boxes and provide minimal interpretability. Their black box nature restricts their use in industries such as aerospace engineering, finance, and law services, where explainability and auditability are critical [12,16]. Managers and engineers might resist the use of AI generated recommendations without knowing the underlying reasons, especially when making decisions that have regulatory or safety implications [11].

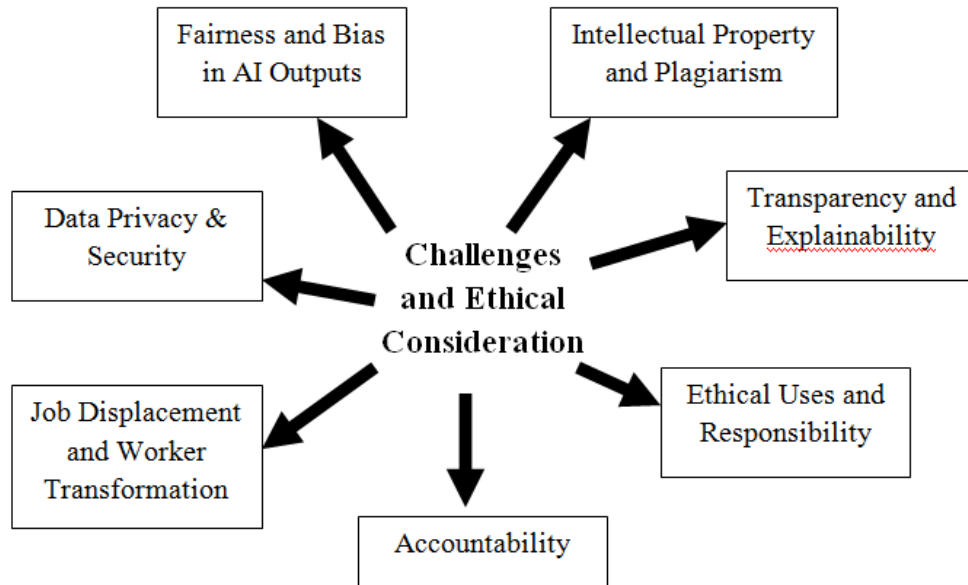


Figure 2: Challenges and Ethical Consideration of Generative AI

E Ethical Usage and Responsibility

The ethical use of Generative AI is still a key issue. Problems such as AI hallucinations (generated data), misinformation, and manipulative content generation can have real world implications, such as faulty business strategies or unsafe engineering choices [5]. The problem is to implement human control, establish responsibility mechanisms, and determine governance procedures that explicitly state accountability for the outcomes of AI [7].

F Job Displacement and Worker Transformation

With Generative AI doing work in engineering design, coding, customer service, and content development, job displacement fears are on the rise. Though AI creates new jobs (e.g., prompt engineering, AI ethics), it jeopardizes conventional jobs, particularly those with predictable, repetitive tasks [1,17]. Companies should invest in re skilling employees to collaborate with AI systems and transition smoothly to AI enhanced roles [9,14].

5. Case Studies and Real World Implementations

A Engineering Applications

AI tools have been incorporated by Boeing into its aircraft design to test and simulate components virtually, taking significantly less time and money than earlier design cycles. Generative AI helps with structural optimization by designing lighter and more efficient components according to safety regulations [7,11]. Autodesk's generative design software allows engineers to set design objectives and constraints, and the AI will present them with thousands of possible designs. This has been applied in architecture, automotive, and manufacturing to achieve innovation and sustainability [16]. Siemens employs AI in the analysis of sensor information from industrial machinery, assisting in predicting breakdowns and scheduling maintenance ahead of time. This enhances operational efficiency and lessens downtime in industries such as manufacturing and energy [18].

B Management Applications

IBM has utilized Watson AI to aid HR activities like talent recruitment, employee engagement, and performance administration. Watson is able to determine employee moods, forecast risks of attrition, and recommend customized career paths [9,14]. Amazon uses AI for demand forecasting, inventory control, and logistics optimization. With AI generated insights, the company reduces delivery delays, lowers operation costs, and achieves higher customer satisfaction [5]. Unilever applies AI powered video interviews and game based testing to analyze candidates' cognitive and affective characteristics. LLMs assist in transcribing and analyzing responses from interviews, making the recruitment process faster without bias [4] [6].

C Schools and Research

Stanford incorporates Generative AI into classes so students can work alongside AI tutors that are capable of producing explanations, code snippets, and even laboratory simulation [1]. MIT and AI in Management Education: MIT Sloan School of Management has integrated Generative AI in its curriculum, allowing students to utilize tools that produce market analysis, strategic reports, and financial forecasts. This equips graduates for potential AI enabled management jobs in the future [5,10].

6. Future Directions and Research Gaps

A Enhancing LLM Efficiency and Minimizing Biases

As Large Language Models (LLMs) continue to grow in size and capability, enhancing computational efficiency and reducing inherent bias have become critical research priorities [8,11]. Current models often demand significant computational power, resulting in high energy consumption and environmental costs, while also being influenced by systemic biases present in their training data. Future research should therefore focus on energy efficient modeling strategies including techniques such as quantization, pruning, and knowledge distillation to reduce resource usage without compromising performance [2,6]. Additionally, bias mitigation approaches are essential, emphasizing the use of diverse, high quality datasets and the adoption of fairness aware learning algorithms to ensure more equitable outcomes [5,11]. Another promising direction lies in

the development of hybrid AI systems, which integrate rule based reasoning with statistical learning to minimize hallucinations and enhance decision reliability, particularly in complex engineering and management applications [8,12].

B Block chain and IoT Integration for Added Security

Combining Generative AI with cutting edge technologies such as Block chain and the Internet of Things (IoT) can strongly improve data security, transparency, and operational resilience [1,7].

Encouraging directions for research include, Blockchain for data provenance, guaranteeing auditability and integrity in AI output through tamper proofed records [7]. AI enabled IoT analytics to drive real time monitoring and predictive maintenance in industries such as smart manufacturing and infrastructure [5]. Decentralized AI systems that decrease dependence on central servers, enhancing privacy and fault tolerance [1,14].

C Ethical AI Governance Models and Policy Recommendations

As the adoption of Artificial Intelligence (AI) in sensitive sectors continues to grow, the need for robust ethical governance models has become increasingly critical. Policies must emphasize fairness, accountability, and transparency to ensure responsible and trustworthy AI deployment [10,14]. Future research and development should focus on establishing uniform ethical AI guidelines that promote responsible AI use across both engineering and management domains [5,10]. Additionally, there is a pressing need for regulatory frameworks to address issues related to liability, intellectual property, and risks arising from automation [7]. Equally important are explainability frameworks that can translate complex AI decisions into humanly understandable terms, thereby fostering trust and accountability, particularly in high risk applications [5,10].

D The Role of Human AI Collaboration in Decision Making

While analytical and predictive capacities are being improved by AI systems, contextual judgment and ethical reasoning continue to depend on human oversight [17]. Research in the future may look at human in the loop systems to support joint decision making in strategies and product design [16,17], AI powered workforce extension, with AI as a copilot for expert professionals in planning, operations, and design [15], AI infused training programs to re skill technical and managerial staff for successful human AI collaboration [12].

7. Conclusion and Recommendations

A Summary of Key Findings

This paper has explored the revolutionary role of Generative AI and LLMs in management and engineering, noting opportunities, challenges, and new use cases.

Some of the key findings include:

1. Engineering innovations from AI powered design, simulation, predictive maintenance, and digital twin deployments.
2. Management transformation through process automation, market prediction, decision support systems, and customer personalization.
3. Challenges and risks, such as algorithmic biases, excessive energy consumption, disinformation, cybersecurity issues, and ethical challenges.
4. Applications in the real world, with companies such as Tesla, Google, and Amazon leveraging AI to promote innovation and efficiency, and universities incorporating LLMs for pedagogy and research.

B Industrial and Academic Practical Implications

The integration of LLMs and Generative AI tools is highly consequential for industry and academia. For industry, the businesses can gain significant operational benefits from automation

and decision making by AI. These, however, need to be supported by strong governance in order to counter ethical threats. For academia the educational institutions must integrate AI literacy into teaching programs and promote cross disciplinary research on themes like explainability, data governance, and AI ethics.

C Policy Recommendations for Responsible AI Deployment

To enable responsible deployment of AI technologies, policymakers need to focus on to establish legal frameworks for algorithmic bias, data protection, and AI accountability, particularly in regulated sectors such as healthcare and finance. Impose explainability and transparency guidelines to ensure that AI systems provide insight into how they make decisions. Support shared governance models, engaging academia, industry, and government in determining AI deployment norms and make AI risk assessments mandatory before implementation in mission critical sectors.

D Future Scope of Research in Generative AI

Despite rapid advancements, several research gaps still persist. These include optimization for efficiency, particularly in terms of energy minimization and model simplification cross technology integration, exploring how AI can interact with emerging technologies such as Block chain, IoT, and quantum computing to enhance capabilities and human–AI collaboration methodologies, emphasizing augmented intelligence rather than complete automation. Furthermore, ensuring fairness and trust in AI remains a key challenge, requiring the development of effective de biasing methods and transparent algorithmic designs. Addressing these gaps will be crucial to unlocking the full potential of Generative AI in management and engineering driving innovation while upholding ethical and responsible deployment.

References

- [1] I. Goodfellow, J. Pouget Abadie, M. Mirza, et al., “Generative adversarial nets,” *Advances in Neural Information Processing Systems*, vol. 27, pp. 2672–2680, 2014.
- [2] A. Vaswani et al., “Attention is all you need,” *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, pp. 5998–6008, 2017.
- [3] OpenAI, “GPT-4 technical report,” arXiv preprint, arXiv:2303.08774, 2023.
- [4] T. Brown et al., “Language models are few-shot learners,” *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 33, pp. 1877–1901, 2020.
- [5] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint, arXiv:1810.04805, 2018.
- [6] H. Touvron et al., “LLaMA: Open and efficient foundation language models,” arXiv preprint, arXiv:2302.13971, 2023.
- [7] Y. K. Dwivedi et al., “Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” *International Journal of Information Management*, vol. 68, p. 102591, 2023.
- [8] S. Chatterjee, N. P. Rana, K. Tamilmani, and A. Sharma, “The role of AI in operations: A review,” *Information Systems Frontiers*, vol. 23, no. 3, pp. 1–17, 2021.
- [9] K. Benke and J. Gu, “Digital twin for metrology,” *Advanced Engineering Informatics*, vol. 48, p. 101296, 2021.
- [10] L. Floridi and J. Cowls, “A unified framework of five principles for AI ethics,” *Minds and Machines*, vol. 32, no. 1, pp. 1–15, 2022.
- [11] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, “On the dangers of stochastic parrots,” in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT ’21)*, pp. 610–623, 2021.
- [12] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. Pearson, 2010.
- [13] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [14] D. P. Kingma and M. Welling, “Auto-encoding variational Bayes,” arXiv preprint, arXiv:1312.6114, 2014.
- [15] Z. Zhang et al., “AI-assisted structural design using deep learning and GANs,” *Automation in Construction*, vol. 137, p. 104203, 2022.
- [16] Y. Pan et al., “Deep reinforcement learning for smart manufacturing,” *Journal of Manufacturing Systems*, vol. 54, pp. 469–479, 2020.
- [17] S. S. Sundar and J. Kim, “Machine agency in human–machine communication: Conceptualizing a triadic interaction model,” *Journal of Computer-Mediated Communication*, vol. 24, no. 3, pp. 84–98, 2019.
- [18] D. Ivanov and A. Dolgui, “Viability of intertwined supply networks: Extending the supply chain resilience angles,” *International Journal of Production Research*, vol. 58, no. 10, pp. 2904–2915, 2020.