

Khameel B. Mustapha¹, Eng Hwa Yap², and Yousif Abakr¹

¹Department of Mechanical, Materials and Manufacturing Engineering, University of Nottingham

²Wawasan Open University

February 26, 2024

Bard, ChatGPT and 3DGPT: A Scientometric Analysis of Generative AI Tools and Assessment of Implications for Mechanical Engineering Education

K.B. Mustapha^{1a}, Eng Hwa Yap^b, Yousif Abakr^a

^aDepartment of Mechanical, Materials and Manufacturing Engineering, University of Nottingham (Malaysia Campus), 43500 Semenyih, Malaysia

^bChancellery, Wawasan Open University, 10050 Penang, Malaysia

Abstract

Following the recent rise in generative artificial intelligence (GenAI) tools, fundamental questions about their wider impacts have started reverberating around various disciplines. To this end, this work was undertaken: (i) firstly, to track the unfolding landscape of general issues surrounding GenAI tools; (ii) secondly, as an exploratory inquiry to elucidate the specific opportunities and limitations of GenAI tools as part of the technology-assisted enhancement of mechanical engineering education and professional practices. As part of the investigation, we conduct and present a brief scientometric analysis of recently published studies to unravel the emerging trend on the subject matter. Further, experimentation was done with selected GenAI tools (Bard, ChatGPT, DALL.E, and 3DGPT) for mechanical engineering-related tasks. The study identified several pedagogical and professional opportunities and guidelines for deploying GenAI tools in mechanical engineering. Besides, the study highlights some pitfalls of GenAI tools for analytical reasoning tasks (e.g., subtle errors in computation involving unit conversions) and sketching/image generation tasks (e.g., poor demonstration of symmetry).

Keywords: Generative AI; ChatGPT; Bard; 3DGPT; Mechanical Engineering; Engineering Education

¹Corresponding author. Telephone: +60387253482, E-mail: KhameelB.Mustapha@nottingham.edu.my (K.B. Mustapha)

1. Introduction

A key demand for students and educators in the 21st century is digital competency [1, 2]. Lately, the dizzying development in the generative artificial intelligence (GenAI) ecosystem has expanded the boundary of digital competency required to thrive in the unfolding AI-centric world. However, our understanding of the far-reaching pros and cons that this new chapter in digital competency portends across various domains is only just taking shape. To underscore this, a string of recent studies and commentaries in this area [3-8] have revealed how the discourse around GenAI risks has triggered policy measures to confront the hard question of what to do with these tools. Yet, while many of the prior studies have conveyed the menacing impact of GenAI tools on the education industry and various business sectors [9-11], this work is motivated by the fact that there are still some grey areas that demand further attention.

Thus, this paper attempts to cast a spotlight on the possible consequential implications of this development for Mechanical Engineering. Concretely, the paper engages with the examination of the potential of these tools to serve as part of the broader instruments for enhancing mechanical engineering education and professional practices.

The remainder of this paper is organized into three main sections as outlined below:

- **Section 2** provides a short historical background of LLMs – the core technology behind the recent progress in GenAI.
- **Section 3** highlights the gap in the literature, hints at the parallel between GenAI tools and MOOC, and introduces a brief bibliometric analysis of recently published studies to sieve through the trend of the academic discussion on the subject matter.
- **Section 4** discusses the implication of GenAI tools for mechanical engineering education, focusing on specific domain applications, challenges, and guidelines. Furthermore, this section showcases the results of our experimentation with Bard, ChatGPT and 3DGPT for mechanical engineering-related tasks.

2. From stochastic parrots to intelligent machines

By definition, a GenAI tool leverages knowledge of the pattern and distribution in its underlying training data to generate synthetic artefacts [12-14]. Such synthetic artefacts can take the form of texts to other forms such as sound, video, waveform, etc. Contrasting with traditional AI tools, GenAI tools concentrate on content creation via instructional input called “prompt” [15]. In essence, many GenAI tools are heralded by development in large language models (LLM), an outgrowth of natural language processing (NLP), which itself represents a strand of machine learning (ML) [16]. Interestingly, language modelling, which now signifies the establishment of an unsupervised ML model trained on word tokens [17], is historically a decades-old idea envisioned in the 1949 seminal work of Shannon [18]. Due to constraints, earlier implementations of language models were largely restricted in scope. They were mostly utilized for machine translation and automatic speech recognition [17]. Indeed, as recent as 2021, LLMs were regarded as “stochastic parrots”, a metaphor coined by Bender, et al. [19] to connote that LLMs are probabilistic statistical models merely repeating the texts on which they are trained with no inherent understanding of the world. However, nowadays, the latest incarnation of language models that evolved into LLM have gained phenomenal ability, despite the diverging philosophical opinions that have emerged regarding how these systems can be described [20, 21].

Developed in the form of conversational agents, recent LLMs-powered applications have demonstrated sophistication in a broad class of text-based related tasks. This includes question-answering, conversations, coding, writing essays, summarizing, etc. [22, 23]. However, beyond textual information generation, these tools have also achieved remarkable achievement with the generation of simple to advanced artistically-constructed images, animations, audio, videos, audio-video contents such as films, etc [24]. Functionally, the capacity of these applications is driven in large part by the quartet of a large corpus of training data, enhanced computer hardware, high-capacity ML models with hundreds of millions/billions of parameters, and state-of-the-art training architecture premised on the Transformer-based Deep Neural Network (DNN) [25-28]. Table 1 highlights a few of the recent notable LLMs and the corresponding massive parameters that characterized them.

Table 1: A highlight of recent LLM and the corresponding number of parameters

Year of Release	Model	# Parameters	Company
2023	GPT-4	~100 trillion	OpenAI
2023	PaLM-2 [29]	540 billion	Google
2023	LLaMA-1 [30]	65 billion	Meta
2023	LLaMA-2 [30]	70 billion	Meta
2023	Falcon-40B [31]	40 billion	TII
2022	ChatGPT	20 billion	OpenAI
2022	BLOOM [32]	176 billion	BigScience
2021	Megatron-Turing NLG	530 billion	Nvidia/Microsoft
2020	GPT-3 [33]	175 billion	OpenAI

Uniquely, LLMs are task-agnostic, unlike traditional AI models developed narrowly for classification, regression, clustering/recommendation tasks [34-37]. Consequently, LLMs are endowed with various fascinating and unexpected emergent behaviours that are not hard-coded during the training process [33, 38]. A recognition of this emergent behaviour has culminated in the repurposing of LLMs as the building blocks for various downstream tasks beyond text generation. Furthermore, it has also resulted in the recent suggestion to refer to LLMs as “foundational models” [26]. Presently, most foundation models or LLMs are owned by large corporations as revealed in Table 1 (as supported by the recent survey by Chen, et al. [39]). Thus, on account of steep technical expertise, direct use of LLM by the wider public is unsurprisingly low.

Lately, the democratization of LLM usage has seen an upward trajectory with the availability of LLM-powered applications. ChatGPT (Chat Generative Pre-Trained Transformer) typifies the capability of LLM-powered applications. Markedly, since the release of ChatGPT, a host of other related LLM-powered applications have since become accessible to the public, some of which are listed in Table 2. The rapid increase in the quality of these tools has spurred scholarly scrutinization of their second-order effect from different angles. The line of ongoing scholarship ranges from those considering the socio-environmental perspectives [40-44], utilitarian dimensions covering drug discovery [45], ethical use in scientific research [46, 47], alignment with human value [48], to adversarial misuse [49-51], among others.

Table 2: A short list of recently announced LLM-powered applications.

Tasks	Examples of LLM-powered Applications
Writing	ChatGPT, Bard, Anthropic Claude 2, Sourcely , LitMap , InstaText , Scholarcy
Semantic/Conversational Search	PerplexityAI , Bing Chat, Vectara , Scite.AI
Copywriting	Jasper , Copy.ai , CopySmith
Coding	GitHub Copilot , OpenAI Code Interpreter, DeepMind's Gato, Claude 2
Image generator	Microsoft Designer , DALL-E 2 (via http://bing.com/create), Lexica , MidJourney , RunwayML , Adobe Firefly
Video generator	Pictory , Synthesia , InVideo
Audio generator	Descript, Synthesys , Listnr, Speechmaker, WaveNet, Respeecher
Drug discovery	BioNeMo , Menten.AI
Translation	DeepL , Reverso Context
3D printing	3DGPT

3. Perspectives on LLM-powered generative AI tools on education

3.1 Gap in Literature

This paper is closely related to the literature on the implications of generative AI tools such as ChatGPT for post-secondary education. Overall, the study contributes to the nascent body of literature dissecting issues around GenAI/ChatGPT by building on studies by Lo [3], Nikolic, et al. [52], Pursnani, et al. [53], Gill, et al. [54], and Bahroun, et al. [55] among others. Notably, many of the aforementioned studies have largely touched on the implications of ChatGPT for general education. Yet, despite attempts to address issues around GenAI in prior studies, there are still subfactors specific to different disciplines that need to be untangled. Consequently, this paper embarks on examining the implications of these tools with a focus on the nuances of their utility for mechanical engineering education and professional practices.

Furthermore, as mentioned by Eke [24], ChatGPT is not the first or only GenAI tool, even though its capability in the generation of intelligent responses, human-level fluency in text summarization, and impressive performance with a host of other NLP-related tasks has catapulted GenAI into the spotlight. More importantly, therefore, this paper experiments with a mix of LLM-powered applications from different companies (*Bard* from Google, *ChatGPT* from OpenAI, *DALL.E* from Microsoft, and *3DPGT* from Authentise) on selected prompts of relevance to the field of mechanical engineering.

In what follows, subsection 3.2 emphasizes the parallel between the popularity of GenAI tools and Massive Online Open Courses (MOOC). Coupled with that, subsection 3.3 presents the outcome of the bibliometric analysis of published studies, and subsection 3.4 distils the evolving general perspectives on ChatGPT/GenAI tools.

3.2 Reflection on the similarity between GenAI and MOOC for education

Given the rapid breakthrough in GenAI, it is safe to hypothesize that the 2020s will be the year that GenAI tools go mainstream, which is analogous to the rise and popularization of Massive Online Open Courses (MOOCs) in the early 2000s. Indeed, as with MOOCs, GenAI tools have received massive coverage in the popular press and sparked critical academic discourse [56]. Similarly, the growth of MOOCs and GenAI can be observed to be driven largely by the wide availability of computing devices and network effects [57]. For instance, as of May 19, 2023, ChatGPT recorded over 1 billion page visits and currently has over 173 million global users, a number that has been growing since its launch in November 2022 [58]. Besides, MOOC and GenAI are: (i) envisioned to achieve the promise of personalized learning at scale; (ii) touted to unleash the democratization of knowledge consumption; and (iii) posit to curtail the closedness of knowledge in traditional education enterprises, among others [59-61]. Furthermore, MOOC and GenAI have been suggested as tools that present opportunities to lessen the burden of teaching on teachers while helping students to take responsibility for their learning [60, 62].

Nonetheless, while MOOCs focused predominantly on content delivery, GenAI tools are developed towards content generation. Moreover, whereas MOOC is often favourably viewed as a revolutionary technology that altered the economies of education [63], GenAI tools such as ChatGPT have elicited a mixture of emotions [64]. Indeed, palpable concerns about these tools have led to many countries, universities, and journals devising rules of engagement or rules for accountability for their use [65-68].

3.3 Bibliometric mapping of related studies on opportunities for learning, teaching, and research

This section distils the issues arising from the potential proliferation of these tools. Specifically, to understand the breadth of research on the subject matter, this section is devoted to the outcome of a scientometric/bibliometric analysis conducted concerning articles at the intersection of ChatGPT, GenAI and education.

To digress slightly, bibliometric or scientometric analysis offers a powerful framework for network analysis of knowledge domains as highlighted by Albort-Morant, et al. [69]. Leveraging advanced

mathematical and data visualization techniques, scientometric analysis has catalysed easy identification of key trends and emerging areas within various fields of studies in the past few years [70-73].

To clarify, there are many essential elements of scientometric analysis. However, the current study focused mostly on cluster and co-occurrence word analyses towards uncovering research clusters and key emerging issues. Figure 1 portrays a brief outline of the steps employed for data curation towards the analysis conducted for the current study.

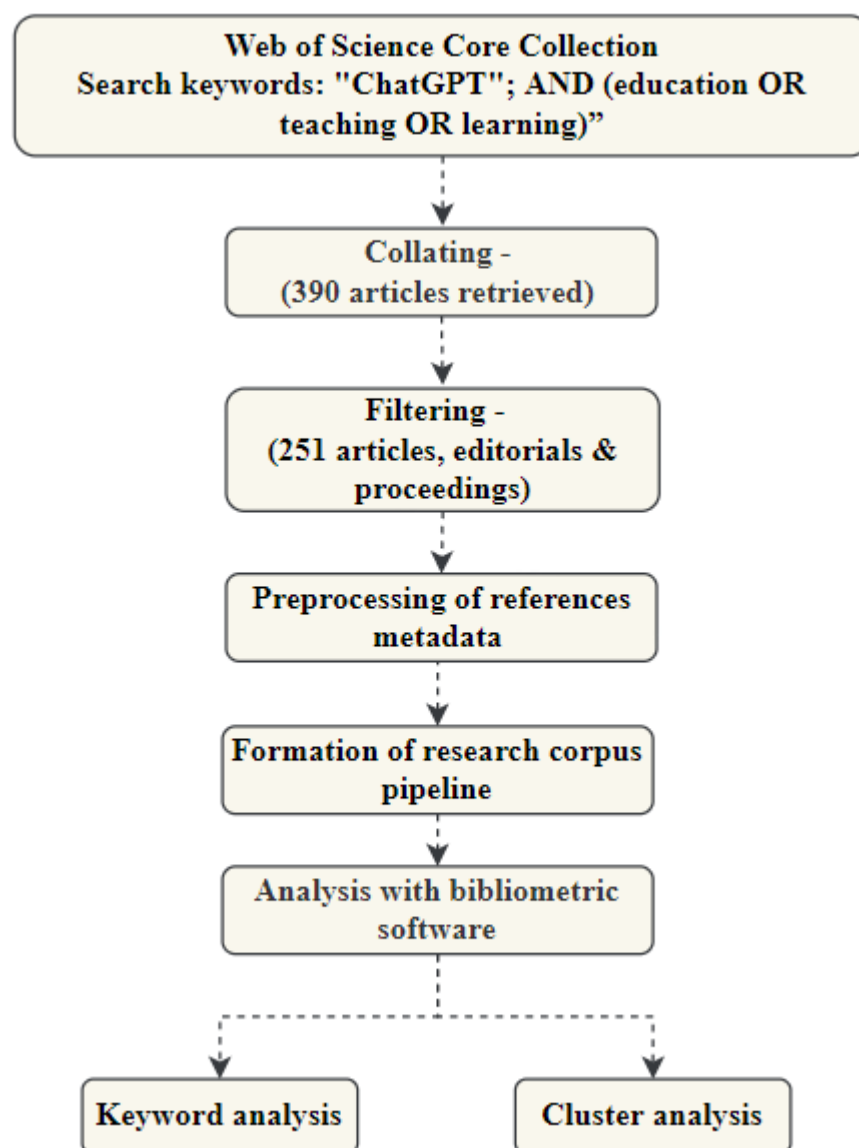


Figure 1: Literature search for scientometric analysis

As the figure shows, the search of the bibliographic records was conducted within the database of the Clarivate Analytics Web of Science [74], which is known to contain a wide coverage of reliable research articles [75]. The last search of the bibliometric data was conducted on the 5th of August 2023, returning over 390 items, a strong indication of the rapid pace of research in this area over a short period. Articles related to news items, magazines and those unrelated to education, teaching and learning were filtered out, leaving just 251 research items comprising research articles, proceedings, and editorials. For the analysis of the metadata, we paired the *R* bibliometric package (*bibliometric*) with VOSViewer [76, 77].

Figure 2 highlights the top 25 subject areas with at least five publications each (as at the time of the data collection), providing a comprehensive overview of the research trends. It is seen that a large subset

of the published articles fall under medical-related fields, which is consistent with the observation of Hariri [78].

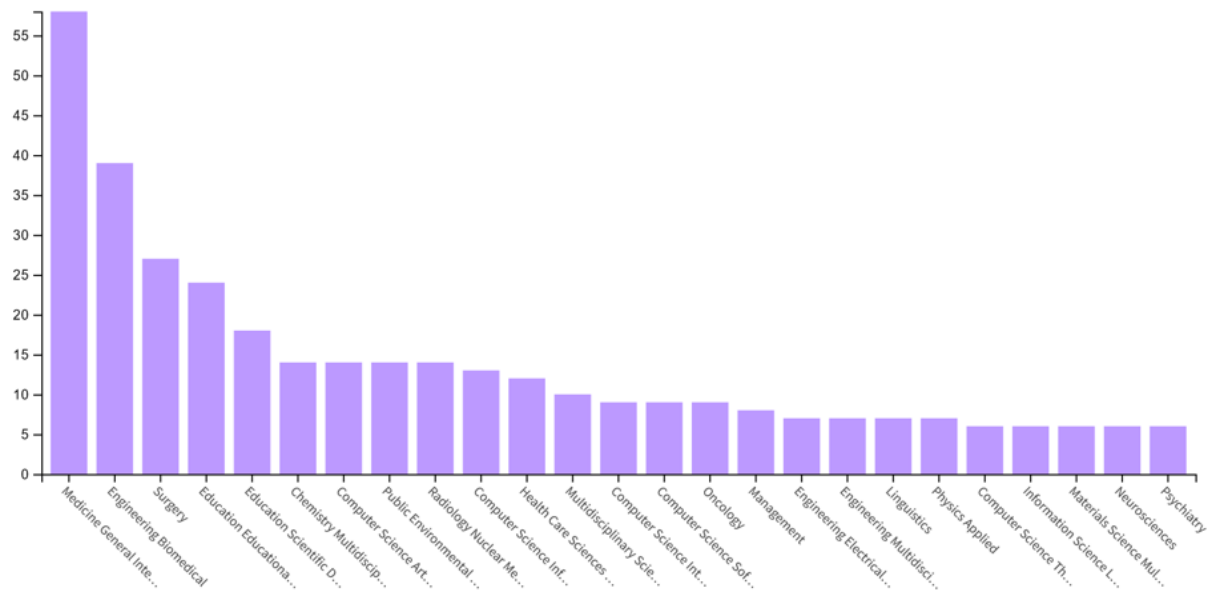


Figure 2: Distribution of the top 25 fields (with at least 5 articles)

Figures 3 - 4 are products of the co-occurrence word analysis. These plots relate to the keywords employed in the curated corpus of articles. Notably, keywords serve as one of the important features of published documents and generally encapsulate the central themes within a particular knowledge domain [79]. In all, the analysis retrieved 748 keywords and VOSviewer is employed to gain insights into the relationships between these keywords.

Pertinently, for a word to appear as a node in the network and cluster map (Figures 3 - 4), it must occur at least 5 times within the aggregated published studies (this is known as a *minimum number of occurrences*) [69]. By setting the minimum number of keywords to 5, only 31 words out of the 748 keywords met the threshold. Therefore, in Figure 3, the size of each node is proportionate to the frequency with which the corresponding keyword appears in the published articles. Meanwhile, greater distance between nodes suggests a less intense connection between the related concepts. Thus, Figure 3 shows the interconnectedness between these 31 keywords, while Figure 4 offers a glimpse into the various subtopics and specialized areas of inquiry on the subject matter. Further, the distinct colour schemes in Figure 4 are used to represent different knowledge domains, as identified through the clustering technique of VOSviewer. Table 3 shows some of the prominent keywords and the strength of their frequency in the aggregated data. Put together, Figures 2 – 4 and Table 3 revealed the existence of much less work on the examination of the implication of this tool from the perspective of engineering education.

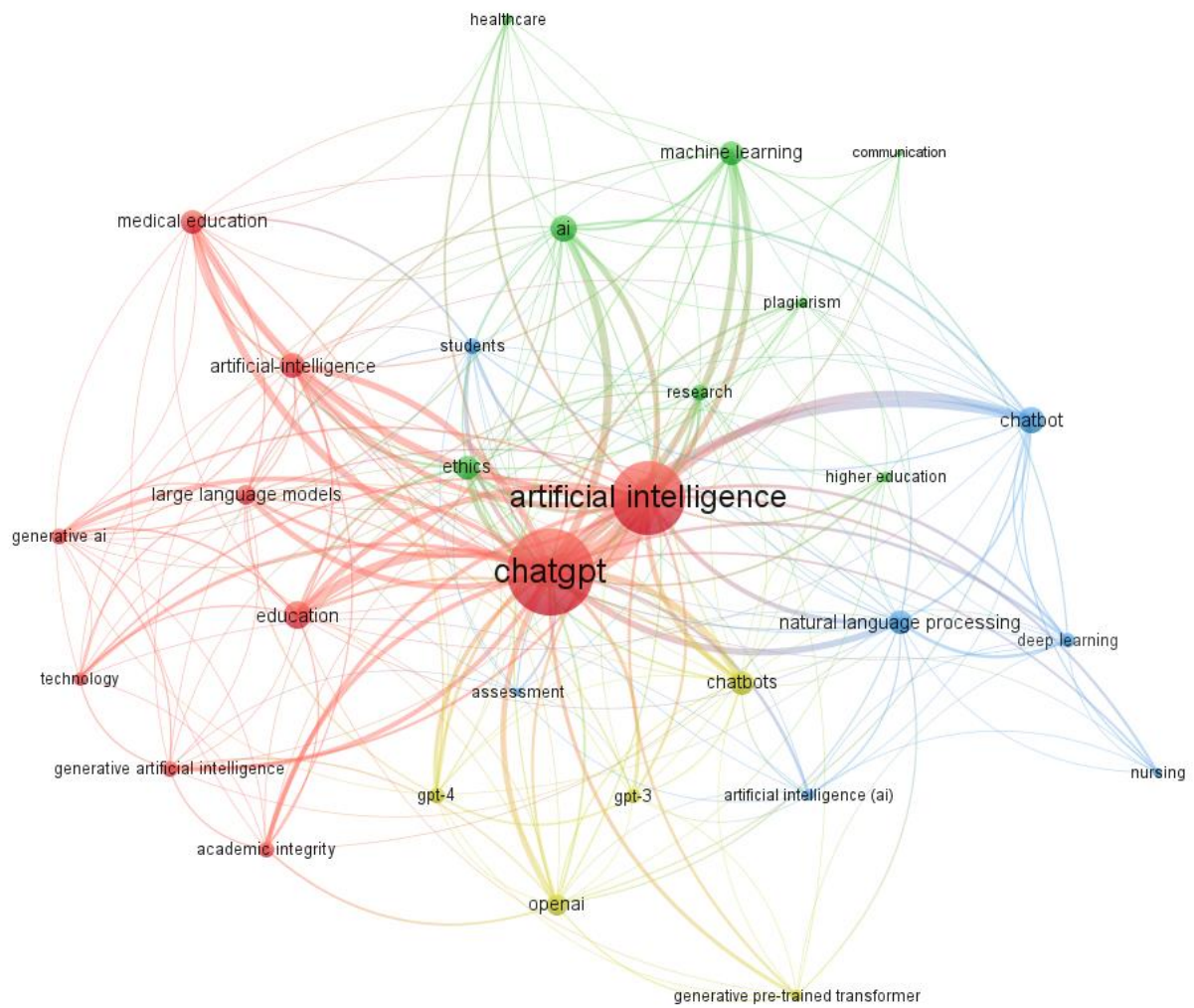


Figure 3: Network of related keywords in published studies on ChatGPT/GenAI and education. Each node in the network map identifies a keyword occurring at least 4 times, while the size of the node is proportional to the number of occurrences of that term.

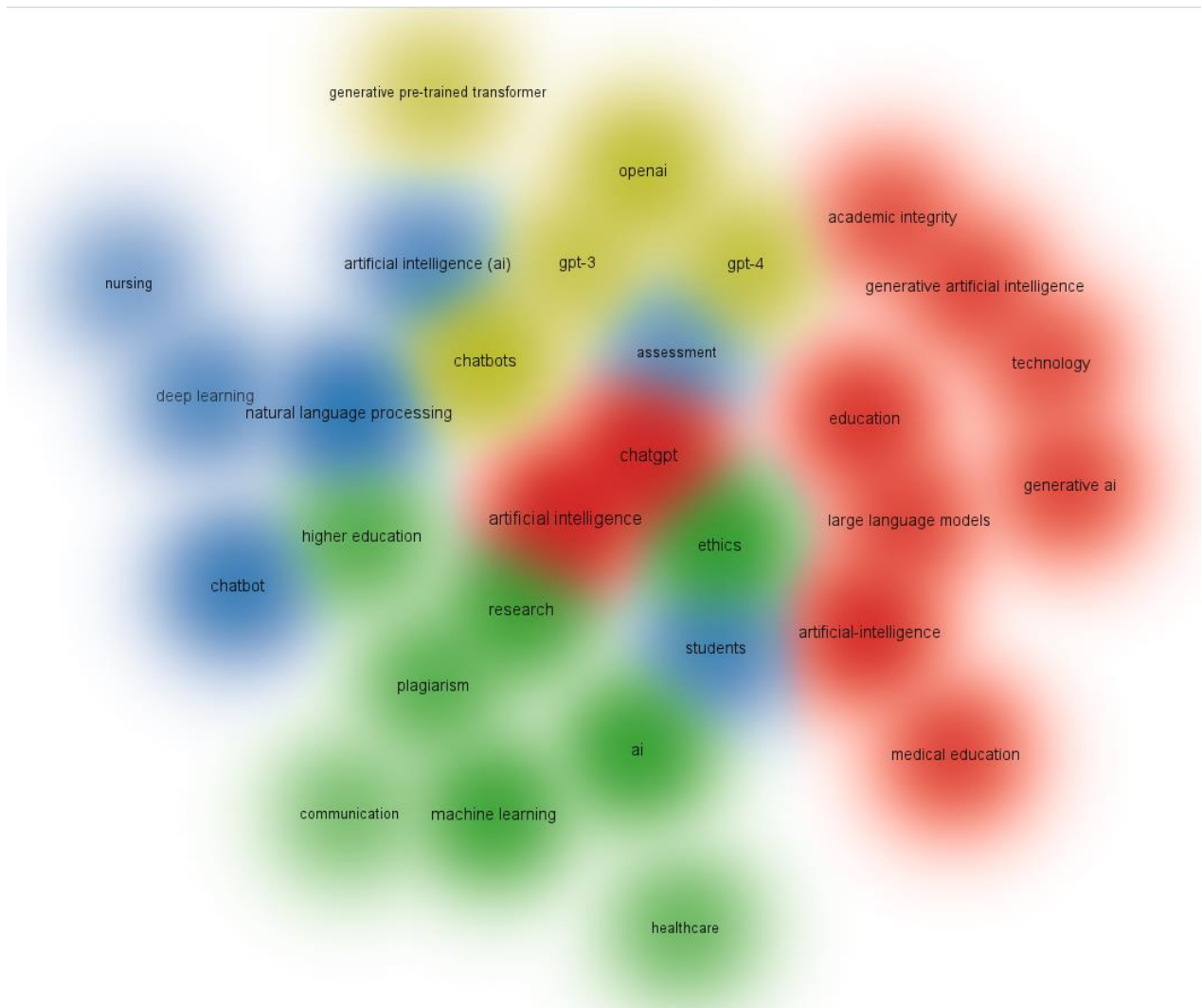


Figure 4: Cluster map of sub-domains in the published studies on GenAI and education

Table 3: List of prominent keywords within the set of curated metadata

Keyword	Total Strength
ChatGPT	321
Artificial Intelligence	271
Chatbot/Chatbots	108
Large Language Models	71
Education	61
Generative Artificial Intelligence	58
Machine Learning	52
Natural Language Processing	51
Medical education	50
Ethics	49
OpenAI	42
gpt-4	31
Academic Integrity	31
Students	29
Deep Learning	26
Generative Pre-trained Transformer	21
Higher Education	16
Plagiarism	16
Assessment	12

3.4 Evolving opportunities and ethical dimensions

As shown in Table 3 and Figures 3-4, some keywords (apart from those related to AI and ML) have dominated the literature on the subject matter: “*education*”, “*higher education*”, “*medical education*”, “*plagiarism*”, “*assessment*”, “*academic integrity*”, and “*ethics*”. Broadly, these keywords reflect the aspirational opportunities of ChatGPT/GenAI for education and key areas of concern that unfolded following the release of ChatGPT [80].

For a good sense of the literature, we now summarize key perspectives from selected studies towards unveiling a broader understanding of the overall landscape. To begin with, we highlight the studies by Kasneci, et al. [22] and Dwivedi, et al. [81]. These two studies present rigorous transdisciplinary exploratory perspectives that wrestled with fundamental questions bordering on the pedagogical, operational, and ethical usage of GenAI tools on the larger educational landscape.

Concretely, Kasneci, et al. [22] reviewed studies at the intersection of education and LLMs and highlighted a breadth of opportunities and challenges of LLM and LLM-powered tools at all levels of education (primary, secondary, tertiary, and professional). In contrast, the opinion piece by Dwivedi, et al. [81], which comprised 43 contributions from authors across 5 continents, provides in-depth coverage of ChatGPT's transformative ramifications across society and disciplines (banking, IT industry, ethics, and education). The work by Farrokhnia, et al. [5] invoked the SWOT analysis framework to offer insight into the strengths/opportunities and weaknesses/threats of ChatGPT. More recently, Tiwari, et al. [82] examined a series of influencing factors that underpinned students' adoption of ChatGPT.

Other studies are more discipline-specific. For instance, Pavlik [83] reflected on the capacity and limitations of ChatGPT for journalism and media education. Jablonka, et al. [84] presented concrete examples of how GenAI tools can be used to transform material science. Lahat, et al. [85] showcased the use of GenAI tools for identification of top research areas in gastroenterology. Peng, et al. [86] highlighted its use for evidence-based medicine, while Lund, et al. [87] discussed the benefit of using ChatGPT for scholarly publishing. The work by Moore, et al. [88] and Biswas [89] explored applications in chemistry education and public health, respectively. Put together, the above studies

identified several obvious and unintended implications of GenAI tools for teaching, learning and research. Some of the opportunities, issues and challenges are outlined below.

3.4.1 Opportunities for learning, teaching and research.

As far as opportunity is concerned, the pedagogical use of chatbots such as ChatGPT and GenAI are expected to bring concrete benefits across different aspects of the education landscape. A few of the opportunities/strengths and weaknesses/challenges associated with GenAI tools as noted in the surveyed literature are outlined below. They can be used for [4, 6, 81, 84, 90-93]

- Generation of large-scale personalized assessment
- Generation of targeted practice problems from course materials
- Automatic quiz generation tailored to a student's level of knowledge
- Provision of explanation of complex texts to ease understanding of study materials
- Provision of real-time and personalized feedback for assessment
- Development of an inclusive learning environment, for example through integration with text-to-speech or speech-to-text facilities
- Enhancement of the development of domain-specific skills such as programming
- Help in the editing of writing tasks
- Text mining (e.g., legal documents, medical reports, etc.)
- Provision of assistance to teachers in stages of lecture preparation, delivery, and assessment
- Deployment as virtual assistant for technical support in service-oriented businesses

3.4.2 Ethical issues, risks, and challenges

As reflected in the bibliometric analysis of section 3.3, academic integrity and assessment are two fundamental virtues of academia that seemed poised to be challenged by these tools. But as already highlighted by Van Dis, et al. [65] and Guersenzvaig and Sánchez Monedero [94], there is a tinge of inevitability to the use of various GenAI tools as they keep increasing in maturity and sophistication. Nonetheless, despite the astonishing progress in the development of LLM-powered tools, much of the GenAI technology is still largely imperfect. Consequently, several criticisms have been put forth.

Earlier criticisms appeared to centre around issues of unintended behaviour from these models (such as propagation of misinformation, social bias, toxicity, and fabrication) to the impact of the huge parameters on the environment [95-97]. However, a summary of other unfolding salient points about the threat and concerns around ChatGPT/GenAI tools are outlined below [6, 22, 65, 98, 99]:

- Democratization of plagiarism
- Lowering of cognitive development engendered by overdependence on these tools
- Limitations in the nuances of social context
- Risk of biases in training dataset that can lead to prejudice against minorities
- Spread of misinformation
- The proliferation of junk research undermining scientific progress
- Copyright issue
- Difficulty in distinguishing between real knowledge and unverified model output
- Erosion of theoretical development
- Dangerous acceptance of unverified AI-generated medical advice/counsel

Coupled with the above, in recent times, “hallucination” has also been found to be an important limitation of ChatGPT and GenAI tools. In short, hallucination is the “generation of plausible strings of text that is factually incorrect”, but which appear coherent on the surface. This behaviour has led to situations where these tools get summarization tasks wrong [65] or simply invent facts, such as fake references [100]. Among others, Borji [101] and Hariri [78] recently presented a compilation of some of the epic failures/limitations of ChatGPT attributable to hallucination.

4. Implications of GenAI tools for Mechanical Engineering

The foundation for sound professional practice stipulates that engineering professionals and students must be trained to be adaptive experts as they navigate the complex interface between the engineering profession and society at large.

Thus, the philosophical foundation of this section rests on a basic premise: that as engineering graduates transition to post-University life, they will likely be confronted with tasks oriented towards finding solutions to some of the 21st-century global grand challenges and diverse societal problems requiring technical solutions [102]. Tackling these challenges and problems will undoubtedly require a repertoire of competencies.

Attempts to instil competencies in preparing students for life as part of the future workforce have led to the adoption of various initiatives such as outcome-based education (OBE), project-based learning, CDIO (Conceive-Design-Implement-Operate), etc [103-105]. However, the skills, knowledge, and technologies that the future workforce will need are likely to be beyond the boundary of that acquired within the four walls of institutions of higher education [99]. Therefore, with the growing digitalization of modern life, GenAI tools may well be one of these tools. Hence, it is only natural to re-imagine the training and assessment procedures that underpin the larger engineering education.

So far, only a handful of studies have set out to examine the implication of ChatGPT on the broader engineering education. Specifically, it is worth highlighting the study by Nikolic, et al. [52]. The authors reported a multi-disciplinary and multi-institutional study on the implication of ChatGPT for general engineering education assessments. Sánchez-Ruiz, et al. [106] examined the role of ChatGPT in the reinforcement of mathematical concepts. Qadir [4], Johri, et al. [8], Berdanier and Alley [107] and Menekse [7] discussed areas of applications/concerns and encouraged engineering educators and policymakers to explore strategies for the ethical and efficient integration of AI tools across diverse aspects of the engineering education. Analyses by Carvallo and Erazo-Garzón [108] and Kwan [109] showed how ChatGPT can be employed as a micro-learning tool for Requirement Engineering and Engineering Statistics. More recently, Frenkel and Emara [110] compared the capabilities of the free and paid versions of ChatGPT on the junior/senior Fundamentals of Engineering Exam in Mechanical Engineering. The authors found that the paid version got 25% more correct answers than the free version. Besides, it was also reported that the acceptance of text-only input by both versions of ChatGPT is a hindrance to their performance on such examinations.

Interestingly, there are still a few grey areas that remain uncovered. For this reason, relative to the prior studies, this section contains a deep dive into the applications of GenAI tools for mechanical engineering education and professional practices.

4.1 GenAI-infused applications for mechanical engineering education and practices

There is a tight connection between number crunching and the engineering field [111]. Incidentally, the field of mechanical engineering is one of the branches of engineering with heavy mathematics-related contents scattered across fundamental subjects such as Mechanics of Materials, Thermodynamics, Fluid Mechanics, Machine Design, Vibration, etc [112]. Thus over the years, in response to technological progress, methods of doing number crunching in this field have evolved from manual to machine-based calculations assisted by various types of computing devices (analogue computers, simple calculators, digital computers, etc.) [113, 114]. Indeed, computing technologies have permeated the field of mechanical engineering to become essential instruments for modelling, design, analysis and manufacturing of complex, large-scale components and systems [115], leading to an active area of research [116].

Understandably, there are still palpable concerns about GenAI tools. However, it cannot be denied that these tools have recently reached an inflection point [117], and it is envisaged that they will become part of the broader computer-assisted teaching techniques that can be leveraged to create exceptional learning experiences for engineering students. Therefore, from a long-term perspective, it is argued that a forward-thinking approach to reshaping engineering education in response to the GenAI-induced transformative shift will involve contemplating the integration of these tools into our methods of

equipping students. In other words, these tools can be leveraged to solve tangible engineering challenges. This is consistent with the argument recently made by Peres, et al. [68]. Further, the pedagogical embrace of these new technological innovations to facilitate students' learning should be cautiously evaluated similarly to: (i) software programs for computer-aided engineering (CAE) (e.g., software for finite element analysis, computational fluid dynamics, etc.); and (ii) software programs for improving mathematical competencies such as MATLAB, Wolfram Mathematica, GeoGebra etc. [118, 119]. For instance, mechanical drafting used to be a predominantly manual activity, but has now been almost completely replaced by tools like AutoCAD [120]. Nevertheless, the pedagogical utility of any new technologies will come with pros and cons. Thus, before adoption and full embrace, the trade-offs for using GenAI tools must be weighed with respect to teaching, learning and research. For once, an important caveat is that most consumer GenAI tools like ChatGPT were not specifically trained on important mechanical engineering-related data, and most are neither developed nor critically tested by mechanical engineering experts. In effect, the output of these tools in response to mechanical engineering-related prompts can thus be error-prone, as will be shown in subsection 4.5, and as also recently revealed by Zhavoronkov [121] for biomedicine. In other words, for the time being, reconciling the output of GenAI tools with factual engineering observations/concepts will still require critical human intervention. Crucially, in response to the shortcomings of the general-purpose GenAI tools, it is believed that the proliferation of mechanical engineering domain-specific LLM-powered applications will continue to evolve.

With the above in mind, the next subsection explores some of the other potential upsides, challenges, and guidelines for the use of these tools for mechanical engineering-related practices.

4.1.1. AI-enhanced rapid formative assessment

The efficacy of assessment feedback as a crucial scaffolding instrument in the development of effective learning and quality teaching in higher education is well-established [122]. At the moment, the student-centred approach to learning requires educators to provide constant feedback to students on their progress through assessments. However, the existing model of assessment in most engineering programs is often predominantly hinged on summative assessment [123]. Providing feedback on summative assessment has been termed *assessment of learning* [124]. With summative assessments, the feedback provided to students is backward-looking. However, if learning is said to be achieved through the quality of teacher-student interaction in learning tasks, as asserted by Black and William [122], then summative assessment tasks ought to be supplemented by formative assessment tasks that can be used for *assessment for learning*. Unfortunately, developing a comprehensive series of formative assessment tasks could be time-consuming without assistance and adequate resources. In this regard, the use of LLM-enabled GenAI that is rigorously fine-tuned on the contents of specific subjects can be a game-changer in allowing lecturers to incorporate personalized exercises that revolve around the fundamental concepts of the subject's learning outcomes [125, 126]. With proper tailoring of such a tool for low-stake tests as proposed by Mollick and Mollick [91], students will be able to instantly identify their current state of progress and get instant feedback from the LLM-powered GenAI system. A simple framework demonstrating the idea is shown in Figure 5.

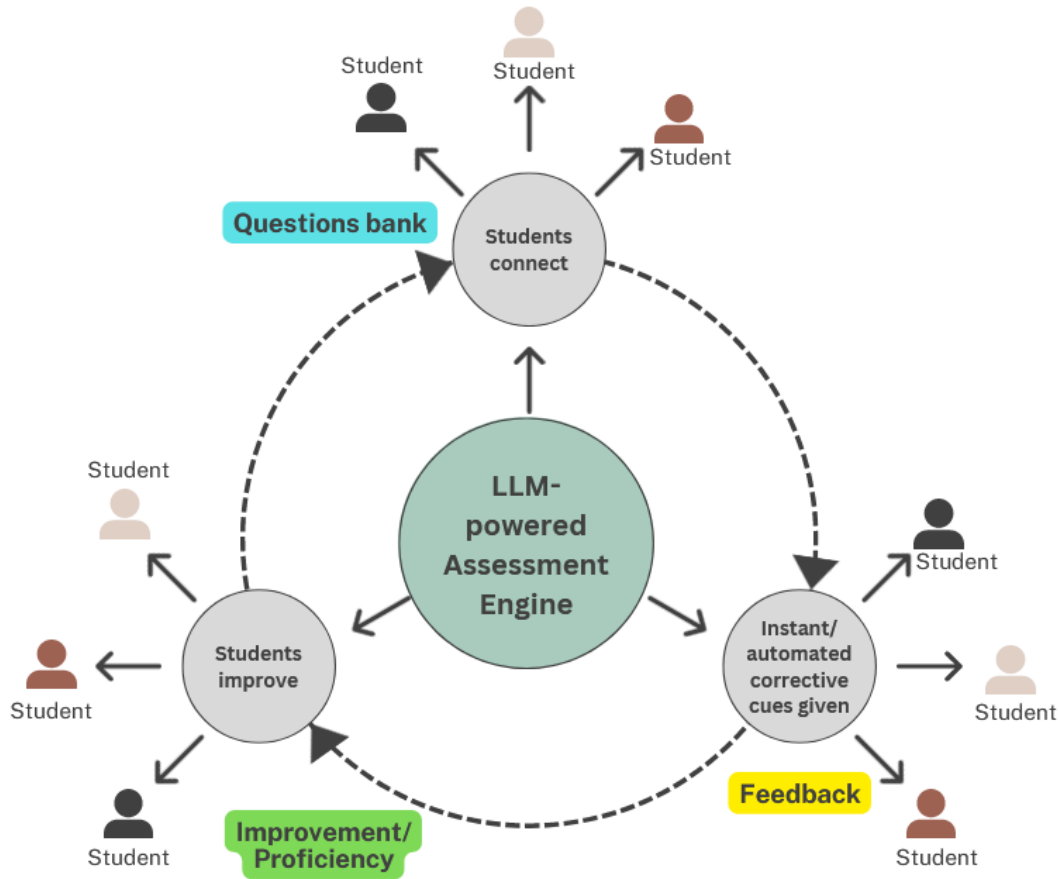


Figure 5: A proposed framework for the “assessment for learning” using LLM/GenAI

4.1.2 AI-powered search engine for material discovery and selection

Selecting appropriate engineering materials with suitable properties is often essential for successful product design outcomes. As a result, in the context of designing machine components or assemblies in mechanical engineering, material discovery and selection involves conducting thorough research on various material options and evaluating their performance against specific project requirements [127]. During the process of material selection, engineers must consider a wide range of factors (strength, thermal stability, fatigue resistance, durability, corrosion resistance, cost, etc.) when making these decisions. Moreover, they need to identify reliable suppliers who can provide consistent quality and timely delivery. Overall, this process requires careful consideration and attention to detail to achieve the selection of cost-effective, best-performing, and easily-available material. Traditionally, this task often entails costly research involving careful examination of supplier datasheets and relevant industry handbooks, etc [128, 129]. In the past, simple libraries have been devised to help in this process [130], but they are often limited in scope [131]. Hence, the recent development could pave the way for custom-designed, LLM-powered conversational applications that can compress the time for this process, thereby speeding up the product development cycle and shortening market lead time.

4.1.3 AI-assisted decision support system for manufacturing

Conversational LLM-powered applications can also play an important role in manufacturing. For instance, Authentise (a UK-based digital company) recently released 3DGPT with the interface shown in Figure 6. It is claimed to have been trained on 12,000 journal articles and additive manufacturing standards [132]. LLM-powered applications such as 3DGPT may represent the future of decision support systems for additive and general manufacturing processes that can be used by engineers, makers, and 3D printing enthusiasts. Another recent example is *Éncy*, developed by SprutCAM Tech [133], which is a chat-based AI assistant designed to make process-generated G-code human-readable. In all, tools like 3DGDT and *Éncy* could serve as alternatives to the drudgery of pouring through dozens

of references and hundreds of pages of documentation in search of answers to basic troubleshooting problems within manufacturing shopfloors. Indeed, Badini, et al. [134] recently showcased a brilliant use-case that involves training ChatGPT on 3D printer G-code and then using it to optimize the G-code to sidestep issues such as warping, stringing, and bed attachment in Fused Deposition Modelling.

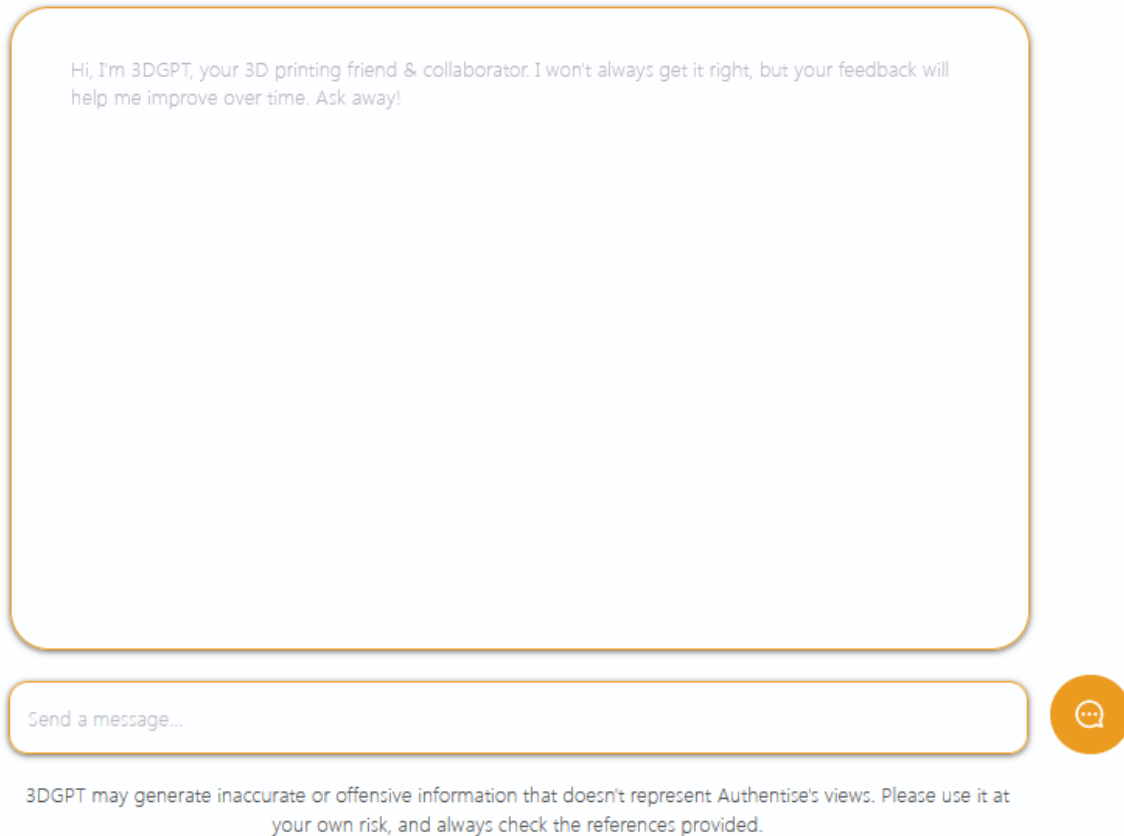


Figure 6: 3DGPT interface

4.1.4 AI-augmented technical documentation

Effective documentation of technical details is crucial for: (i) preserving records of procedures; (ii) conveying complex ideas between teams working on a project; and (iii) communicating with an audience with non-engineering backgrounds [135]. Besides, in a corporation with teams distributed over the world, internal communication is a key pillar of product development as highlighted by Sosa, et al. [136]. In this regard, the integration of LLM-powered GenAI tools, such as ChatGPT, holds the potential to expedite internal and external communication. Such tools can smoothen the process of connecting the dots between technical details, ease the generation of technical documents, and help with the simplification of complex ideas.

For example, one could envision an engineering firm embarking on an innovative technical project. As the project progresses and engineers across the teams produce intricate project details, a conversational GenAI can be developed to transform their inputs into comprehensive reports for internal communication. The tool can also help in preserving technical nuances while also distilling the project details into user-friendly manuals for a broader audience. Another specific use case is in the preparation of a report for product positioning. Specifically, given descriptions of multiple competitor products, tools like Bard and ChatGPT could help generate detailed market reports, considering the spectrum of subfactors in the market segment. Of course, a critical inspection of such final reports should be carried out to avoid problems of hallucinations that come up in other areas [10].

4.1.5 AI-enabled acceleration of product design workflow

In brief, engineering product design often comes down to a few main steps encapsulated in Figure 7. On the one hand, a rich set of state-of-the-art tools (such as ANSYS, SOLIDWORKS, Abaqus, Cosmos,

Autodesk Inventor, etc.) have already been integrated at various levels of undergraduate engineering studies [137]. Nonetheless, these tools are meant to cater only partially for the intermediate stages of the design process (detailed modelling, virtual prototyping, product structural analysis, and optimization). On the other hand, GenAI tools can empower engineers in some tasks related to a majority of the design phases shown in Figure 7.

First, engineers can employ these tools to accomplish creative problem framing, which is usually a critical aspect of the idea-generation step of product development [138]. Second, GenAI tools can assist during the conceptual design synthesis phase of product development. For instance, engineers can feed the functional requirements of a product to tools such as Bard/ChatGPT which can act as a brainstorming partner towards innovative design concepts. Such tools can also be used for quick feasibility assessments and idea validation.

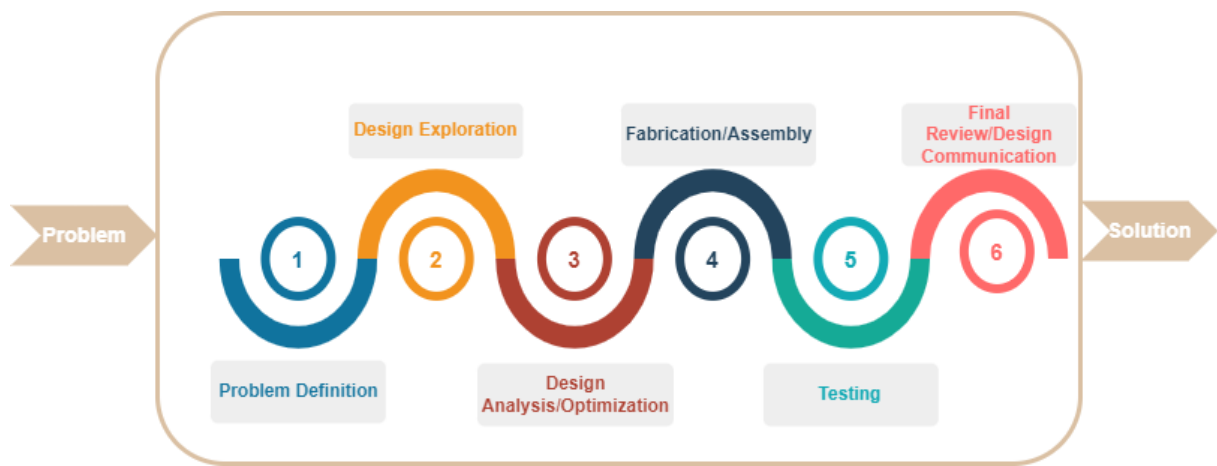


Figure 7: Engineering design process

Besides, image-based GenAI tools like DALL.E can be leveraged to quickly create initial virtual sketches of ideas as a starting point for downstream iteration as done in Figure 8(a) or to generate varied photorealistic images of products for marketing briefs as shown in Figure 8(b). It should be noted that as with text-based generators like ChatGPT, image generators also suffer from many subtle errors. In the authors' experimentation with these tools (as of August 2023), a common mistake is found to be a lack of symmetry in the generated image. For instance, two obvious errors (a technically inaccurate tire and a missing tire) are indicated in Figure 8(b). Also, the front tires in Figure 8(a) are unequal in size. Nonetheless, these tools will continue to improve. Furthermore, the immaculate ability of GenAI tools in summarization can be judiciously employed by engineers to conduct/summarize patent searches, leading to a clear understanding of the technical terrain of prior arts and uncovering relevant concepts from the prior arts.



(a)



(b)

Figure 8: Images generated using DALL.E: (a) created with the prompt(August 2023): “Sketch of a motorized wheelchair in a minimalistic environment”; (b) created with the prompt: “Photorealistic image of a motorized wheelchair in a minimalistic environment”.

4.2 Challenges for using Generative AI tools for Mechanical Engineering

While GenAI tools have the potential to offer valuable support in mechanical engineering education and professional practices, there are several challenges and considerations to be aware of when using them in this field. Some of these challenges are listed in Table 4.

Table 4: Highlight of possible challenges in using GenAI for mechanical engineering tasks

Issues	Description
Limited domain knowledge	Responses from general-purpose GenAI tools are based on the data they have been trained on. In reality, the training data is unexpected to cover the entire breadth of mechanical engineering concepts. Consequently, these tools may lack a deep understanding of specific technical details and nuances, leading to the generation of incorrect/misleading information about specialized mechanical engineering topics. This is demonstrated in section 4.4.
Lack of contextual understanding	Text-based GenAI tools might struggle to fully understand the context of a technical conversation in a cross-functional team. In turn, this might lead to out-of-context responses and hallucination-affected misinterpretation of specific terminology.
Oversimplification	GenAI tools may oversimplify complex engineering concepts, omit crucial technical details, or fail to capture the intricacies of real-world mechanical systems.
Validation of outputs	Technical GenAI-generated solutions warrant scepticism. This demands that such solutions be validated through appropriate engineering methods to avoid dangerous pitfalls. As is now apparent with CAD software, relying solely on GenAI tools without proper testing and validation is likely to lead to unworkable technical designs or decisions.
Copyright issue	For image-based GenAI tools, the issue of copyright remains a major concern (as highlighted in section 3.4). Hence, it is imperative for GenAI-generated images to be carefully scrutinized to avoid copyright violations.
Uncertainty handling in complex system design	At the moment, GenAI tools hardly convey uncertainties or limitations in their responses, potentially leading to overconfidence in their suggestions. Besides, these tools might not consider all aspects of a problem (such as manufacturing feasibility, material constraints, contextual cost implications, compliance with code of practices, etc).

4.3 Developing guidelines for ethical deployment of generative AI tools

With the challenges outlined in section 4.2, it is apparent that deploying generative AI for engineering projects in general and mechanical engineering specifically should be done with careful consideration of ethical principles and responsible practices. Indeed, there will be acceptable and unacceptable use of such tools as emphasized by Qadir [4], and others [139]. Nonetheless, in light of the possible risks associated with these tools, a few inexhaustive guidelines to ensure the ethical deployment of generative AI for mechanical engineering professional practices are outlined here.

First, having a transparent policy will be imperative to reduce the risks surrounding the use of these tools for engineering applications. Across the lifecycle of product development [140], ranging from research, development and service tasks, clear policies on when and how GenAI tools can be used must be implemented. In other words, within engineering enterprises, similar to other industries [26, 141, 142], clear communication and policy on GenAI's role, capabilities, and limitations should be instituted.

Second, oversight (both ethical and regulatory) has always been a crucial socio-technical pillar of the traditional engineering project management framework [143]. In an era where GenAI tools can be seamlessly integrated into various facets of engineering design processes, the significance of human expertise will remain crucial. Therefore, human oversight should be put in place within engineering design firms and engineering education enterprises to question the integrity and reliability of GenAI-generated outputs. Indeed, by mandating that AI-generated outputs undergo rigorous scrutiny by human engineers, engineering design firms not only mitigate the potential risks associated with algorithmic errors/biases but also guarantee that the outcomes align with a project's objectives, industry standards and regulatory concerns. Finally, professional engineers/engineering students will have to ensure that GenAI-generated solutions adhere to ethical/safety standards and the deployment complies with industry regulations.

4.4 Experimenting with some GenAI tools for mechanical engineering-related tasks

This section demonstrates the outcome of experimentations with a few GenAI tools listed in Table 5. The first two tools (Bard and ChatGPT) are considered general-purpose text-based GenAI systems. The third (3DGPT) is a domain-specific GenAI tool, while the last is an image generator. For transparency's sake, the version of ChatGPT employed here is the free version of ChatGPT with GPT3.5 as the backbone LLM (i.e., ChatGPT-3.5). While ChatGPT-3.5 is known to be limited by non-access to the internet and characterized by a knowledge cut-off date of September 2021, it has been adopted here for experimentation due to its free availability to users worldwide.

Table 5: List of GenAI tools tested on mechanical engineering-related prompts

<i>GenAI Tools</i>	<i>Link</i>	<i>Tested Functionality</i>
<i>Bard</i>	http://bard.google.com	Analytical capability
<i>ChatGPT</i>	https://chat.openai.com/	Analytical capability
<i>3DGPT</i>	https://www.authentise.com/3dgpt	Domain-specific text generator
<i>DALL.E</i>	https://www.bing.com/create	Sketches and images of products

Table 6 lists the prompts employed for the analytical evaluations. These questions were inspired by those in the text by Bird and Ross [144]. For each of the prompts, we zeroed in on errors generated by the tools. As indicated in the table, Bard and ChatGPT were evaluated for their ability to solve 5 questions that can be mapped to Year 1 of the Mechanical Engineering degree. It is worth noting that many more prompts were tried, but for space constraints, the responses to these 5 questions are provided as a representative demonstration of the tools' performance. Notably, both Bard and ChatGPT are capable of many more capabilities such as programming, but the focus has been restricted to testing their analytical reasonings, an area they are still known to have some weaknesses [145].

Table 6: Prompts for the analytical reasoning evaluation of Bard and ChatGPT (as of August 2023)

Prompts	Concept	Tool	Correctness of Answer
P1	Statics	ChatGPT	Correct*
		Bard	Correct
P2	Statics	ChatGPT	Inconclusive
		Bard	Incorrect (unit conversion error in the calculation)
P3	Heat energy/transfer	ChatGPT	Correct
		Bard	Correct
P4	Heat energy/transfer	ChatGPT	Correct
		Bard	Incorrect (addition error)
P5	Fluid Mechanics	ChatGPT	Correct
		Bard	Incorrect (multiplication error)

*All the questions tested have solutions that can be deterministically verified from fundamental mechanical engineering concepts/calculations. Hence, correct or incorrect here indicates agreement with or deviation from the fundamental solution procedure.

In response to the first prompt (P1), which connects to the finding of the efficiency of a simple load-multiplying machine, both ChatGPT and Bard produced correct responses as shown in Figures 9 and 10, respectively. The response from Bard is more concise, while that from ChatGPT is a bit wordy, but both largely showed the “reasoning step” to the solution.

Figures 11 – 12 portray the outputs of Bard and ChatGPT to Prompt 2 – finding the efficiency of a pulley-based system. Here, both applications produced unsatisfactory answers that were not necessarily wrong. Interestingly, the mistakes that caused unsatisfactory answers differ for both Bard and ChatGPT. Simply, ChatGPT lacks the understanding of the implicit knowledge that the movement ratio should equal the number of pulleys (highlighted in Figure 11). In contrast, Bard made a benign mistake (highlighted in Figure 12) around unit conversion. At this juncture, it is noted that unit inconsistency when dividing is one of the prevalent mistakes we have noticed with these tools. Although Bard shows more of it in the reported exercises, ChatGPT is also found to be susceptible to this kind of subtle error. The error can be corrected via different prompt engineering exploits, such as chain-of-thoughts, etc [146]. However, we have avoided taking such a route to avoid biasing the naturally yielded answers by the tools.

Figures 13 and 14 represent the outputs in response to a question involving heat capacity. Both applications got the final answer right, and they both provided reasonable explanations of the solution step. Next, the two applications were trialled for two more somewhat harder problems that require an understanding of the difference between latent and sensible heat (Prompt 4 in Table 6). The outputs from the two applications for prompt 4 are depicted in Figures 15 and 16, respectively. Finally, the corresponding responses for prompt 5 are shown in Figures 17 and 18, respectively. For Prompts 4 and 5, ChatGPT was able to determine the correct answers. On the other hand, Bard made some very benign mistakes in the calculation that involved multiplication. Specifically, in Figure 16, Bard forgot to include the value of 20 degrees in the final multiplication of the highlighted expression. Additionally, in Figure 18 it got the value of $v = 24.3 \text{ m/s}$ by doing $(37850)/(2 * 770)$ rather than $\sqrt{((37850 * 2)/770)}$ in the highlighted operation. Despite the mistakes uncovered in this experimentation, the “reasoning” done by these tools is found to be relatively on track. To some degree, it is hoped that uncovering some of the mistakes will contribute to attempts to improve the LLM models powering these tools, as noted elsewhere [147].

Moving on, we test 3DGPT [132], a very recent domain-specific LLM-powered application to troubleshoot a 3D printing problem. As is now well-known, 3D printing has become an integral part of

engineering teaching of late [148]. One of the common issues requiring troubleshooting of material extrusion-based printers is nozzle blockage [149]. To evaluate the ability of 3DGPT, although it remains largely in development, it was given a textual prompt: “List the major causes of nozzle blockage, along with the corrective actions, in fused deposition modelling method”. The generated output in response to the prompt is shown in Figure 19, which is impressive and very much on track with what is expected. Further, an interesting feature of the output from 3DGDP is the inclusion of reference forming the basis of the response spit out by the system. However, as highlighted in Figure 19, this domain-specific GenAI tool is also not immune to error. The first error is providing no name for the author of the second reference, which turned out to be Klahn and Meboldt [150]. Besides, on carefully examining the third reference, it appears not to have anything related to nozzle blockage. Finally, a simple task of generating images for product concept/marketing has already been demonstrated with DALL.E in Figure 8. It was shown that image-based GenAI tools also suffer from many subtle errors such as a lack of understanding symmetry in the generated image or generation of geometrically illogical shape, etc.

Put together, the outcome of the experimentations reported here revealed the growing capabilities of these GenAI tools, despite the few weaknesses highlighted. Going forward, it is expected that these tools will experience sustained development and integrating them into mechanical engineering education and professional practices/workflow may be inevitable in response to the shift in the digital transformation that will be induced by these tools.

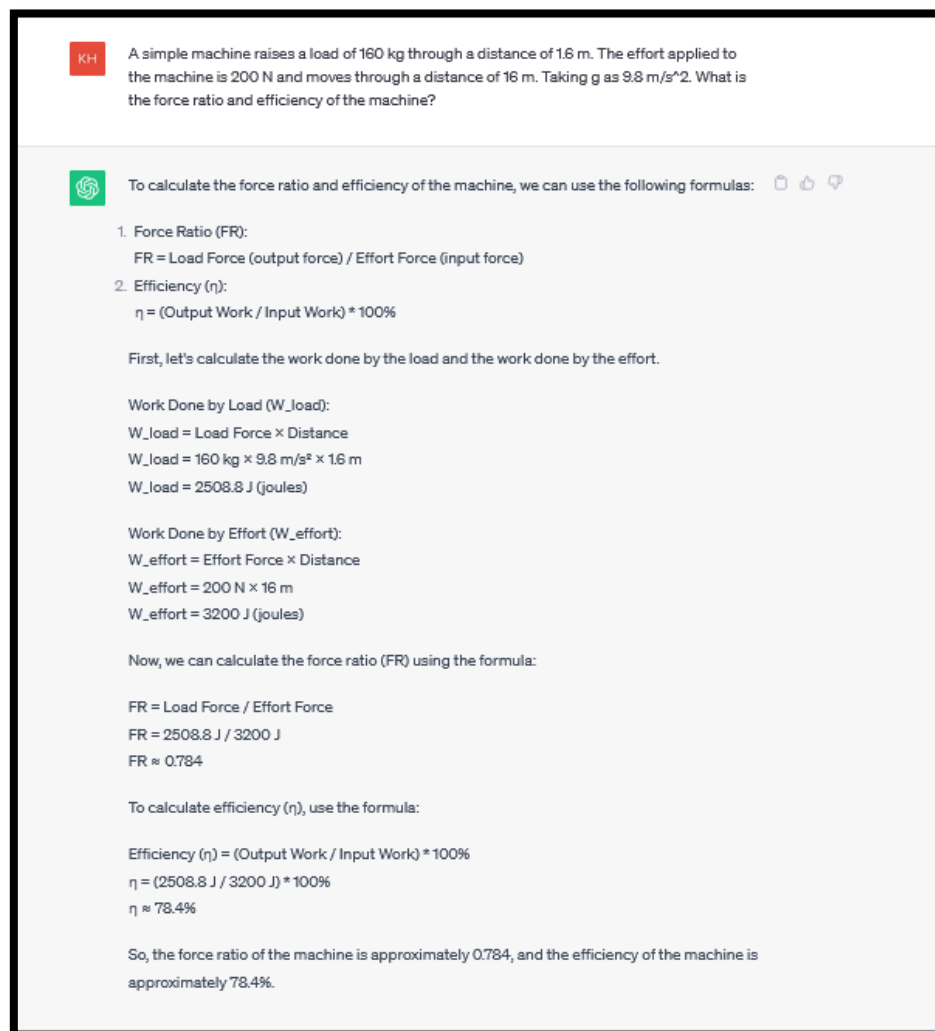


Figure 9: ChatGPT's response to a question on a simple load-multiplying machine

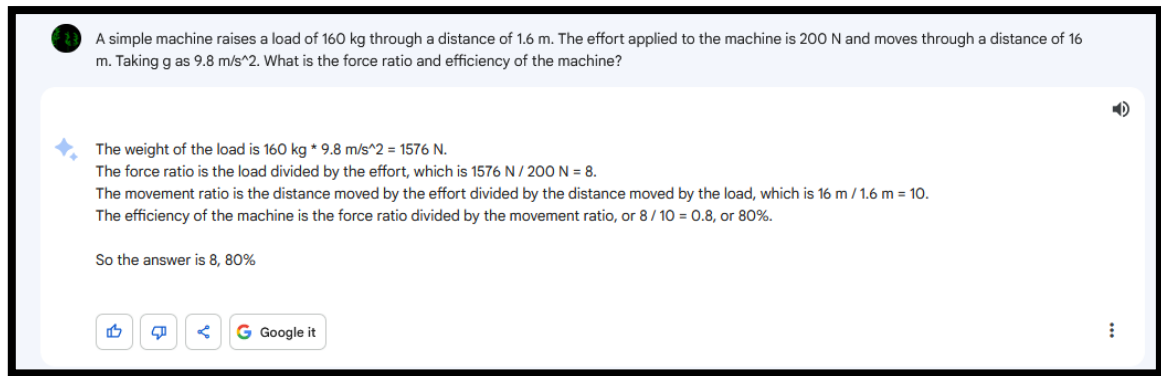


Figure 10: Bard's response to a question on a simple load-multiplying machine

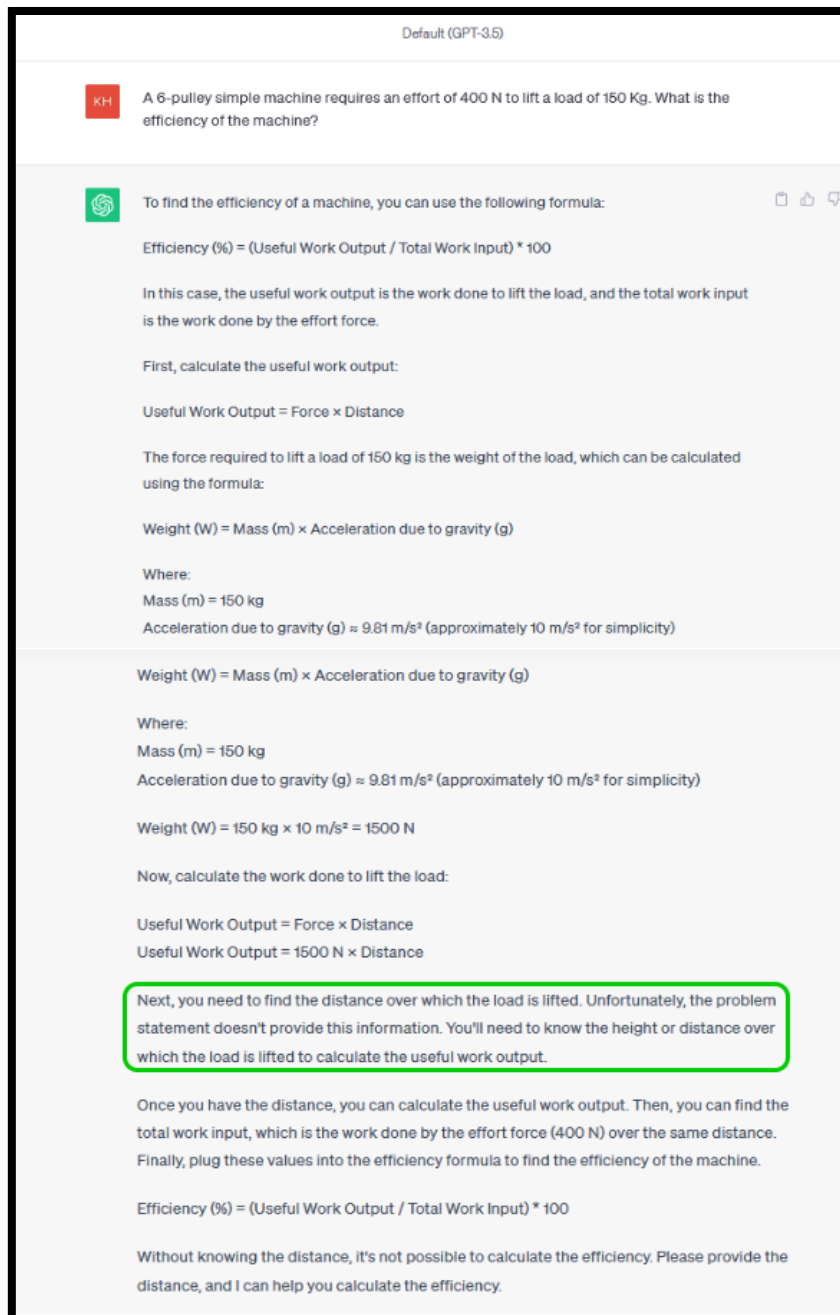


Figure 11: ChatGPT's response to a question on the efficiency of a pulley system

A 6-pulley simple machine requires an effort of 400 N to lift a load of 150 Kg. What is the efficiency of the machine?

The efficiency of a pulley system is calculated by considering the frictional losses in the system.

The efficiency of a 6-pulley system with bushed pulleys is typically around 65-80%. So, the efficiency of the machine in your example is about 70%.

Here is the calculation:

$$\text{Efficiency} = 1 - (\text{Frictional losses} / \text{Input work})$$

The frictional losses in the system are the energy that is lost due to the friction between the moving parts of the system. The input work is the energy that is applied to the system by the effort.

The frictional losses in a 6-pulley system with bushed pulleys are typically around 20-30% of the input work. So, the efficiency of the machine in your example is:

$$\text{Efficiency} = 1 - (0.20 / 1) = 0.80 = 80\%$$

The mechanical advantage (MA) of the machine is the ratio of the load to the effort, or $150 \text{ kg} / 400 \text{ N} = 0.375$. **Mistake**

The velocity ratio (VR) of the machine is the number of times the effort moves for every time the load moves, or 6.

The efficiency of the machine is the MA divided by the VR, or $0.375 / 6 = 0.0625$, or 6.25%.


However, this is not the correct answer. The efficiency of a pulley system is not calculated by dividing the MA by the VR. The efficiency of a pulley system is calculated by considering the frictional losses in the system.

So the answer is 70%

Figure 12: Bard's response to a question on the efficiency of a pulley system

KH

A block of cast iron having a mass of 10 kg cools from a temperature of 150 degree C to 50 degree C. How much energy is lost by the cast iron? Assume the specific heat capacity of iron is 500 J/(kg degree C)



To calculate the energy lost by the cast iron as it cools, you can use the formula for heat energy:

$$Q = m \cdot c \cdot \Delta T$$

Where:

- Q is the heat energy lost (in joules),
- m is the mass of the cast iron (in kilograms),
- c is the specific heat capacity of iron (in joules per kilogram per degree Celsius), and
- ΔT is the change in temperature (in degrees Celsius).

Given:

- Mass (m) = 10 kg
- Specific Heat Capacity (c) = 500 J/(kg·°C)
- Initial Temperature (T_{initial}) = 150°C
- Final Temperature (T_{final}) = 50°C

Now, calculate the change in temperature:

$$\Delta T = T_{\text{final}} - T_{\text{initial}} = 50^{\circ}\text{C} - 150^{\circ}\text{C} = -100^{\circ}\text{C}$$

Now, plug the values into the formula to find the energy lost (Q):

$$Q = 10\text{kg} \cdot 500\text{J}/(\text{kg} \cdot ^{\circ}\text{C}) \cdot (-100^{\circ}\text{C})$$

Now, calculate Q :

$$Q = -500,000\text{J}$$

The cast iron loses 500,000 joules (J) of energy as it cools from 150°C to 50°C.

Figure 13: ChatGPT's response to a question involving heat capacity.

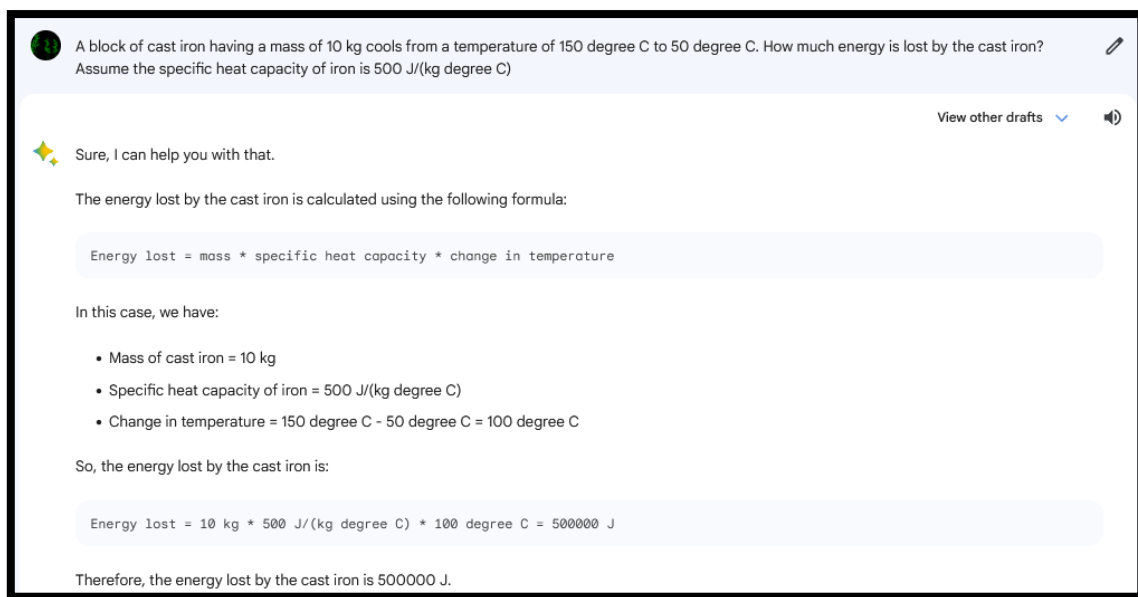




Figure 14: ChatGPT's response to a question involving heat capacity.



What is the heat energy needed to change 400 g of ice, initially, at -20 degree C, into steam at 120 degree C?



To calculate the heat energy needed to change a substance from one state to another with temperature changes, you need to consider the energy required for each step of the process.

Where:

- Q is the heat energy required (in joules),
- m is the mass of the substance (in kilograms), and
- L is the latent heat of the substance (in joules per kilogram).

Let's break down the process into several steps:

- Heating the ice from -20°C to 0°C (to bring it to the melting point):
 - Mass (m) = 400 g = 0.4 kg
 - Change in temperature (ΔT) = 0°C - (-20°C) = 20°C
 - Specific heat capacity of ice (c_{ice}) = 2100 J/(kg·°C)
 - Energy required for this step: $Q_1 = m \cdot c_{ice} \cdot \Delta T_1$
- Melting the ice into water at 0°C:
 - Latent heat of fusion of ice (L_{fusion}) = 333,550 J/kg
 - Energy required for this step: $Q_2 = m \cdot L_{fusion}$
- Heating the water from 0°C to 100°C (to bring it to the boiling point):
 - Specific heat capacity of water (c_{water}) = 4190 J/(kg·°C)
 - Change in temperature (ΔT) = 100°C - 0°C = 100°C
 - Energy required for this step: $Q_3 = m \cdot c_{water} \cdot \Delta T_3$
- Vaporizing the water into steam at 100°C:
 - Latent heat of vaporization of water ($L_{vaporization}$) = 2,257,000 J/kg
 - Energy required for this step: $Q_4 = m \cdot L_{vaporization}$
- Heating the steam from 100°C to 120°C:
 - Specific heat capacity of steam (c_{steam}) = 2010 J/(kg·°C)
 - Change in temperature (ΔT) = 120°C - 100°C = 20°C
 - Energy required for this step: $Q_5 = m \cdot c_{steam} \cdot \Delta T_5$

Now, calculate each step's energy and sum them up to find the total energy required:

$$Q_{total} = Q_1 + Q_2 + Q_3 + Q_4 + Q_5$$

Plug in the values for each step and calculate:

$$Q_{total} = (0.4kg) \cdot (2100J/(kg \cdot ^\circ C)) \cdot (20^\circ C) + (0.4kg) \cdot (333550J/kg) + (0.4kg) \cdot (4190J/(kg \cdot ^\circ C)) \cdot (100^\circ C) + (0.4kg) \cdot (2257000J/kg) + (0.4kg) \cdot (2010J/(kg \cdot ^\circ C)) \cdot (20^\circ C)$$

Now, calculate Q_{total} :

$$Q_{total} = 16800J + 133420J + 167600J + 902800J + 16080J$$

$$Q_{total} = 1121700J$$

The heat energy needed to change 400 g of ice initially at -20°C into steam at 120°C is 1,121,700 joules (J).

Figure 15: ChatGPT's output on a question involving sensible plus latent heat energy.

What is the heat energy needed to change 400 g of ice, initially, at -20 degree C, into steam at 120 degree C?

Sure, I can help you with that.

The heat energy needed to change 400 g of ice, initially, at -20 degree C, into steam at 120 degree C is 411600 J.

The process of changing ice into steam at 120 degree C can be divided into 5 steps:

1. Raising the temperature of ice from -20 degree C to 0 degree C.
2. Melting the ice at 0 degree C.
3. Raising the temperature of water from 0 degree C to 100 degree C.
4. Vaporizing the water at 100 degree C.
5. Raising the temperature of steam from 100 degree C to 120 degree C.

The heat energy required for each step can be calculated using the following formula:

$$\text{Heat energy} = \text{mass} * \text{specific heat capacity} * \text{change in temperature}$$

In this case, we have:

- Mass of ice = 400 g
- Specific heat capacity of ice = 2.108 J/(g degree C)
- Specific heat capacity of water = 4.186 J/(g degree C)
- Specific heat capacity of steam = 2.09 J/(g degree C)
- Latent heat of fusion of ice = 333.55 J/g
- Latent heat of vaporization of water = 2257 J/g

So, the heat energy required for each step is:

Step 1: $400 \text{ g} * 2.108 \text{ J/(g degree C)} * (0 \text{ degree C} - (-20 \text{ degree C})) = 1683.2 \text{ J}$

Step 2: $400 \text{ g} * 333.55 \text{ J/g} = 133420 \text{ J}$

Step 3: $400 \text{ g} * 4.186 \text{ J/(g degree C)} * (100 \text{ degree C} - 0 \text{ degree C}) = 16744 \text{ J}$

Step 4: $400 \text{ g} * 2257 \text{ J/g} = 90280 \text{ J}$

Step 5: $400 \text{ g} * 2.09 \text{ J/(g degree C)} * (120 \text{ degree C} - 100 \text{ degree C}) = 832 \text{ J}$ **Mistake**

Therefore, the total heat energy required is $1683.2 \text{ J} + 133420 \text{ J} + 16744 \text{ J} + 90280 \text{ J} + 832 \text{ J} = 411600 \text{ J}$.

I hope this helps! Let me know if you have any other questions.

Figure 16: Bard's output on a question involving sensible plus latent heat energy.

KH

A storage tank contains oil with a density of 770 kg/m^3 . The storage tank has an outlet pipe, of diameter 0.04 m , located 5 m from the free surface of the tank. Assuming no losses at the pipe entry, determine the mass flow rate at the exit of the outlet pipe.



To determine the mass flow rate at the exit of the outlet pipe, you can use Torricelli's theorem, which relates the velocity of a fluid exiting an orifice to the height of the fluid column above the orifice. Here's how you can calculate it step by step:



1. Calculate the velocity of the oil at the exit of the pipe using Torricelli's theorem:

$$v = \sqrt{2gh}$$

Where:

- v is the velocity of the oil at the exit of the pipe.
- g is the acceleration due to gravity (approximately 9.81 m/s^2).
- h is the height of the oil column above the outlet of the pipe.

In this case, the height (h) is the distance from the free surface of the tank to the outlet of the pipe, which is 5 m .

$$v = \sqrt{2 \cdot 9.81 \cdot 5} = \sqrt{98.1} \approx 9.9 \text{ m/s}$$

2. Calculate the cross-sectional area of the outlet pipe (A) using the given diameter (d):

$$A = \frac{\pi d^2}{4}$$

$$A = \frac{\pi \cdot (0.04 \text{ m})^2}{4} = \frac{\pi \cdot 0.0016 \text{ m}^2}{4} \approx 0.0012566 \text{ m}^2$$

3. Calculate the mass flow rate (m_{dot}) using the following equation:

$$m_{dot} = \rho \cdot A \cdot v$$

Where:

- m_{dot} is the mass flow rate.
- ρ is the density of the oil (770 kg/m^3).
- A is the cross-sectional area of the outlet pipe.
- v is the velocity of the oil at the exit of the pipe.

$$m_{dot} = 770 \text{ kg/m}^3 \cdot 0.0012566 \text{ m}^2 \cdot 9.9 \text{ m/s} \approx 9.67 \text{ kg/s}$$

So, the mass flow rate at the exit of the outlet pipe is approximately 9.67 kg/s .

Figure 17: ChatGPT's response to the fluid flow problem

A storage tank contains oil with a density of 770 kg/m^3 . The storage tank has an outlet pipe, of diameter 0.04 m , located 5 m from the free surface of the tank. Assuming no losses at the pipe entry, determine the mass flow rate at the exit of the outlet pipe.

Sure, I can help you with that.

The mass flow rate of oil at the exit of the outlet pipe can be calculated using the following formula:

$$\text{Mass flow rate} = (\text{Area of pipe opening}) * (\text{Velocity of oil}) * (\text{Density of oil})$$

The area of the pipe opening is $\pi * r^2$, where r is the radius of the pipe opening. In this case, the radius of the pipe opening is $0.04 \text{ m} / 2 = 0.02 \text{ m}$. So, the area of the pipe opening is $\pi * (0.02 \text{ m})^2 = 0.0012566 \text{ m}^2$.

The velocity of the oil can be calculated using the Bernoulli equation, which states that the energy of a fluid remains constant as it flows. In this case, the energy of the oil is the potential energy due to its height above the ground, plus the kinetic energy due to its velocity.

The potential energy of the oil is mgh , where m is the mass of the oil, g is the acceleration due to gravity (9.8 m/s^2), and h is the height of the oil above the ground (5 m). So, the potential energy of the oil is $770 \text{ kg} * 9.8 \text{ m/s}^2 * 5 \text{ m} = 37850 \text{ J}$.

The kinetic energy of the oil is $\frac{1}{2} mv^2$, where m is the mass of the oil and v is the velocity of the oil. So, the kinetic energy of the oil is $\frac{1}{2} * 770 \text{ kg} * v^2$.

Setting the potential energy of the oil equal to the kinetic energy of the oil, we get:

$$37850 \text{ J} = \frac{1}{2} * 770 \text{ kg} * v^2$$

Solving for v , we get:

$$v = 24.3 \text{ m/s}$$

Mistake

Therefore, the mass flow rate of oil at the exit of the outlet pipe is:

$$\text{Mass flow rate} = (0.0012566 \text{ m}^2) * (24.3 \text{ m/s}) * (770 \text{ kg/m}^3) = 0.0319 \text{ kg/s}$$

So the answer is 0.0319 kg/s .

Figure 18: Bard's response to the fluid flow problem

You : List the major causes of nozzle blockage, along with the corrective actions, in fused deposition modelling method.

3DGPT: The major causes of nozzle blockage in the fused deposition modeling method can include:

1. Filament Jam: This occurs when the filament gets stuck or tangled within the extruder mechanism, preventing it from smoothly flowing through the nozzle.
2. Contaminants: Dust, debris, or foreign particles can enter the filament and clog the nozzle, disrupting the flow of material.
3. Heat-related Issues: If the temperature settings are not properly calibrated, the filament may not melt consistently, leading to blockages.
4. Poor Filament Quality: Low-quality or poorly manufactured filaments can have inconsistencies or impurities that contribute to nozzle blockages.

To address these issues and correct nozzle blockage in fused deposition modeling, the following actions can be taken:

To address these issues and correct nozzle blockage in fused deposition modeling, the following actions can be taken:

1. Clear Filament Path: Check for any obstructions or tangles in the filament path and remove them. Ensure that the filament spool is properly mounted and feeding smoothly.
2. Clean the Nozzle: Use a small wire brush or a specialized nozzle cleaning tool to remove any debris or contaminants from the nozzle. Be careful not to damage the nozzle while cleaning.
3. Check Temperature Settings: Verify that the temperature settings are accurate for the filament being used. Adjust the temperature if necessary to ensure proper melting and flow of the material.
4. Use High-Quality Filament: Invest in high-quality filaments from reputable manufacturers to minimize the chances of impurities or inconsistencies that can lead to blockages.
5. Regular Maintenance: Perform routine maintenance on the 3D printer, including cleaning and lubricating the extruder mechanism, to prevent buildup and ensure smooth filament flow.

By addressing these causes and taking appropriate corrective actions, nozzle blockages in fused

By addressing these causes and taking appropriate corrective actions, nozzle blockages in fused deposition modeling can be minimized, resulting in more reliable and successful prints.

References:

Title: 3D mapping from high resolution satellite images
Authors: D. Goulas, A. Georgopoulos, A. Sarakenos, Ch. Paraschou
Year: 2013.0
DOI: 10.1117/12.2028334

Title: Industrializing Additive Manufacturing
Authors: nan
Year: 2011.0
DOI: 10.1007/978-3-030-54334-1

Title: Application of Micro-Scale 3D Printing in Pharmaceuticals
Authors: Andrew Kjar, Yu Huang
Year: 2019.0
DOI: 10.3390/pharmaceutics11080390

Reference

Figure 19: 3DGPT's response for troubleshooting of nozzle blockage

5. Conclusion

This study has presented a short bibliometric evaluation that helped in crystallizing the emerging issues concerning generative artificial intelligence (GenAI) tools as typified by ChatGPT. Altogether, a short bibliometric mapping of related studies was presented. Further, the presentation identified elements of potential applications of GenAI tools for the field of mechanical engineering. A few findings from the analysis and inquiry are outlined below:

- Section 2 revealed that large language models are still largely owned by large corporations, but widespread use is taking place via consumer-facing apps like ChatGPT, Bard, etc.
- In section 3:
 - The cluster analysis undertaken via the scientometric assessment showed a high publication density about ChatGPT/GenAI tools in medical-related fields. This suggests a very intense and active research in this field compared to others, but also indicates the need for more rigorous assessments of GenAI tools through the lenses of other sub-fields.
 - The scientometric assessment also uncovered keywords that capture the unfolding potential benefits (e.g., personalized feedback, inclusive learning environment through integration with text-to-speech or speech-to-text GenAI tools, etc) and highlight the significant concerns (spread of plagiarism, loss of integrity, etc.) of ChatGPT/GenAI tools in education.
- In section 4:
 - The assessment of the implications of GenAI tools for the field of mechanical engineering drew connections between GenAI tools and other computing technologies that have enhanced the field such as MATLAB, SOLIDWORKS, etc.
 - Possible use cases for leveraging GenAI tools for mechanical engineering were highlighted. This encompasses the acceleration of product development tasks such as material selection/discovery, manufacturing troubleshooting, technical documentation, to product positioning, among others.
 - Experimentation with Bard and ChatGPT on selected analytical problems revealed that these tools exhibit sound reasoning in the solution steps. Nonetheless, they also generated errors in a few instances that unmasked their lack of understanding of implicit domain knowledge.

Despite the above findings, the work is not without limitations. First, the rapid pace of publication in this area means that the breadth of coverage of the papers that formed the basis of the bibliometric analysis was limited to those covered by the data curation period. Second, GenAI tools that were tested such as Bard, ChatGPT, DALL.E, and 3DGPT are constantly being updated. This means some of the issues highlighted as weaknesses at the time of the test may be corrected in future versions of these tools. Third, GenAI tools are stochastic machines. In other words, the same prompts tested by the same user at different times may yield an unidentical output. Lastly, the performance of GenAI tools can always be enhanced by extensive prompt engineering tricks. However, for the sake of reproducibility, the authors avoided goading these tools towards the right answer using advanced prompt engineering techniques.

In all, it is hoped that the findings from this study will help strengthen the belief that the prospect of matured GenAI tools is something institutions and professional societies cannot wave away. Hence, as institutions, educators, companies, and professional bodies put in place anticipatory policies for this transformative technology, this paper holds the view that charting the middle course of cautious embrace will hold more benefit than outright banning these tools.

Acknowledgment

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors gratefully acknowledge Alphabet Inc for free use of Bard, OpenAI for the free use of ChatGPT, and Authentise Inc for the free use of 3DGPT.

Since submission of this article, the second author has updated his affiliation: Eng Hwa Yap is now at the **Chancellery, Wawasan Open University, Penang, Malaysia**

References

- [1] C. Redecker, "European framework for the digital competence of educators: DigCompEdu," Joint Research Centre (Seville site), 2017.
- [2] L. I. González-Pérez and M. S. Ramírez-Montoya, "Components of Education 4.0 in 21st century skills frameworks: systematic review," *Sustainability*, vol. 14, no. 3, p. 1493, 2022.
- [3] C. K. Lo, "What is the impact of ChatGPT on education? A rapid review of the literature," *Education Sciences*, vol. 13, no. 4, p. 410, 2023.
- [4] J. Qadir, "Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education," in *2023 IEEE Global Engineering Education Conference (EDUCON)*, 2023: IEEE, pp. 1-9.
- [5] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, pp. 1-15, 2023, doi: 10.1080/14703297.2023.2195846.
- [6] M. M. Rahman and Y. Watanobe, "ChatGPT for education and research: Opportunities, threats, and strategies," *Applied Sciences*, vol. 13, no. 9, p. 5783, 2023.
- [7] M. Menekse, "Envisioning the future of learning and teaching engineering in the artificial intelligence era: Opportunities and challenges," *Journal of Engineering Education*.
- [8] A. Johri, A. S. Katz, J. Qadir, and A. Hingle, "Generative artificial intelligence and engineering education," *Journal of Engineering Education*, 2023.
- [9] B. Eager and R. Brunton, "Prompting higher education towards AI-augmented teaching and learning practice," *Journal of University Teaching & Learning Practice*, vol. 20, no. 5, p. 02, 2023.
- [10] S. Milano, J. A. McGrane, and S. Leonelli, "Large language models challenge the future of higher education," *Nature Machine Intelligence*, vol. 5, no. 4, pp. 333-334, 2023.
- [11] M. S. Stiene Riemer, Ella Rabener, Jeanne Kwong Bickford, Pim Hilbers, Nipun Kalra, Aparna Kapoor, Julian King, Silvio Palumbo, Neil Pardasani, Marc Pauly, Kirsten Rulf, and Michael Widowitz, "A Generative AI Roadmap for Financial Institutions," November, 13, 2023. [Online]. Available: <https://www.bcg.com/publications/2023/a-genai-roadmap-for-fis>
- [12] M. Jovanovic and M. Campbell, "Generative artificial intelligence: Trends and prospects," *Computer*, vol. 55, no. 10, pp. 107-112, 2022.
- [13] R. Gozalo-Brizuela and E. C. Garrido-Merchán, "A survey of Generative AI Applications," *arXiv preprint arXiv:2306.02781*, 2023.
- [14] P. Zhu *et al.*, "ERNIE-Music: Text-to-Waveform Music Generation with Diffusion Models," *arXiv preprint arXiv:2302.04456*, 2023.
- [15] H. Dang, L. Mecke, F. Lehmann, S. Goller, and D. Buschek, "How to prompt? Opportunities and challenges of zero- and few-shot learning for human-AI interaction in creative applications of generative models," *arXiv preprint arXiv:2209.01390*, 2022.
- [16] J. Yang *et al.*, "Harnessing the power of llms in practice: A survey on chatgpt and beyond," *arXiv preprint arXiv:2304.13712*, 2023.
- [17] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? ", presented at the Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event, Canada, 2021. [Online]. Available: <https://doi.org/10.1145/3442188.3445922>.
- [18] C. E. Shannon, "A mathematical theory of communication," *The Bell system technical journal*, vol. 27, no. 3, pp. 379-423, 1948.
- [19] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the dangers of stochastic parrots: Can language models be too big?," in *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 2021, pp. 610-623.
- [20] M. Shanahan, "Talking about large language models," *arXiv preprint arXiv:2212.03551*, 2022.
- [21] M. Mitchell and D. C. Krakauer, "The debate over understanding in AI's large language models," *Proceedings of the National Academy of Sciences*, vol. 120, no. 13, p. e2215907120, 2023.
- [22] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, 2023/04/01/ 2023, doi: <https://doi.org/10.1016/j.lindif.2023.102274>.
- [23] E. Mollick and J. Euchner, "The Transformative Potential of Generative AI: A Conversation with Ethan Mollick Jim Euchner talks with Ethan Mollick about generative AI: its potential to transform work and what organizations—and individuals—ought to do... now!," *Research-Technology Management*, vol. 66, no. 4, pp. 11-16, 2023.
- [24] D. O. Eke, "ChatGPT and the rise of generative AI: Threat to academic integrity?," *Journal of Responsible Technology*, vol. 13, p. 100060, 2023/04/01/ 2023, doi: <https://doi.org/10.1016/j.jrt.2023.100060>.
- [25] A. Vaswani *et al.*, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
- [26] R. Bommasani *et al.*, "On the opportunities and risks of foundation models," *arXiv preprint arXiv:2108.07258*, 2021.
- [27] J. Wei *et al.*, "Emergent abilities of large language models," *arXiv preprint arXiv:2206.07682*, 2022.
- [28] T. Lin, Y. Wang, X. Liu, and X. Qiu, "A survey of transformers," *AI Open*, 2022.
- [29] R. Anil *et al.*, "Palm 2 technical report," *arXiv preprint arXiv:2305.10403*, 2023.
- [30] A. Meta, "Introducing LLaMA: A foundational, 65-billion-parameter large language model," *Meta AI*. <https://ai.facebook.com/blog/large-language-model-llama-meta-ai>, 2023.
- [31] E. Almazrouei *et al.*, "Falcon-40B: an open large language model with state-of-the-art performance," *Findings of the Association for Computational Linguistics: ACL*, vol. 2023, pp. 10755-10773, 2023.

- [32] T. L. Scao *et al.*, "Bloom: A 176b-parameter open-access multilingual language model," *arXiv preprint arXiv:2211.05100*, 2022.
- [33] T. Brown *et al.*, "Language models are few-shot learners," *Advances in neural information processing systems*, vol. 33, pp. 1877-1901, 2020.
- [34] H. Wang, J. Li, H. Wu, E. Hovy, and Y. Sun, "Pre-trained language models and their applications," *Engineering*, 2022.
- [35] J. Li, T. Tang, W. X. Zhao, J.-Y. Nie, and J.-R. Wen, "Pretrained language models for text generation: A survey," *arXiv preprint arXiv:2201.05273*, 2022.
- [36] W. X. Zhao *et al.*, "A survey of large language models," *arXiv preprint arXiv:2303.18223*, 2023.
- [37] L. Fan, L. Li, Z. Ma, S. Lee, H. Yu, and L. Hemphill, "A bibliometric review of large language models research from 2017 to 2023," *arXiv preprint arXiv:2304.02020*, 2023.
- [38] A. Narayan, I. Chami, L. Orr, and C. Ré, "Can Foundation Models Wrangle Your Data?," *arXiv preprint arXiv:2205.09911*, 2022.
- [39] H. Chen *et al.*, "ChatGPT's One-year Anniversary: Are Open-Source Large Language Models Catching up?," *arXiv preprint arXiv:2311.16989*, 2023.
- [40] C.-J. Wu *et al.*, "Sustainable ai: Environmental implications, challenges and opportunities," *Proceedings of Machine Learning and Systems*, vol. 4, pp. 795-813, 2022.
- [41] A. S. Luccioni, S. Viguier, and A.-L. Ligozat, "Estimating the carbon footprint of bloom, a 176b parameter language model," *arXiv preprint arXiv:2211.02001*, 2022.
- [42] N. Bannour, S. Ghannay, A. Névéol, and A.-L. Ligozat, "Evaluating the carbon footprint of NLP methods: a survey and analysis of existing tools," in *Proceedings of the Second Workshop on Simple and Efficient Natural Language Processing*, 2021, pp. 11-21.
- [43] M. C. Rillig, M. Ågerstrand, M. Bi, K. A. Gould, and U. Sauerland, "Risks and benefits of large language models for the environment," *Environmental Science & Technology*, vol. 57, no. 9, pp. 3464-3466, 2023.
- [44] A. Abid, M. Farooqi, and J. Zou, "Large language models associate Muslims with violence," *Nature Machine Intelligence*, vol. 3, no. 6, pp. 461-463, 2021.
- [45] A. Blanco-González *et al.*, "The Role of AI in Drug Discovery: Challenges, Opportunities, and Strategies," *Pharmaceuticals*, vol. 16, no. 6, p. 891, 2023. [Online]. Available: <https://www.mdpi.com/1424-8247/16/6/891>.
- [46] A. Birhane, A. Kasirzadeh, D. Leslie, and S. Wachter, "Science in the age of large language models," *Nature Reviews Physics*, vol. 5, no. 5, pp. 277-280, 2023/05/01 2023, doi: 10.1038/s42254-023-00581-4.
- [47] R. Watkins, "Guidance for researchers and peer-reviewers on the ethical use of Large Language Models (LLMs) in scientific research workflows," *AI and Ethics*, pp. 1-6, 2023.
- [48] A. Kasirzadeh and I. Gabriel, "In conversation with Artificial Intelligence: aligning language models with human values," *Philosophy & Technology*, vol. 36, no. 2, pp. 1-24, 2023.
- [49] J. Hazell, "Large language models can be used to effectively scale spear phishing campaigns," *arXiv preprint arXiv:2305.06972*, 2023.
- [50] D. Kang, X. Li, I. Stoica, C. Guestrin, M. Zaharia, and T. Hashimoto, "Exploiting programmatic behavior of llms: Dual-use through standard security attacks," *arXiv preprint arXiv:2302.05733*, 2023.
- [51] M. Mozes, X. He, B. Kleinberg, and L. D. Griffin, "Use of llms for illicit purposes: Threats, prevention measures, and vulnerabilities," *arXiv preprint arXiv:2308.12833*, 2023.
- [52] S. Nikolic *et al.*, "ChatGPT versus engineering education assessment: a multidisciplinary and multi-institutional benchmarking and analysis of this generative artificial intelligence tool to investigate assessment integrity," *European Journal of Engineering Education*, pp. 1-56, 2023.
- [53] V. Pursnani, Y. Sermet, and I. Demir, "Performance of ChatGPT on the US Fundamentals of Engineering Exam: Comprehensive Assessment of Proficiency and Potential Implications for Professional Environmental Engineering Practice," *arXiv preprint arXiv:2304.12198*, 2023.
- [54] S. S. Gill *et al.*, "Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots," *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 19-23, 2024.
- [55] Z. Bahrour, C. Anane, V. Ahmed, and A. Zacca, "Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis," *Sustainability*, vol. 15, no. 17, p. 12983, 2023.
- [56] J. V. Pavlik, "Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education," *Journalism & Mass Communication Educator*, vol. 78, no. 1, pp. 84-93, 2023.
- [57] Z. Katona, P. P. Zubcsek, and M. Sarvary, "Network effects and personal influences: The diffusion of an online social network," *Journal of marketing research*, vol. 48, no. 3, pp. 425-443, 2011.
- [58] D. F. Carr, "ChatGPT Grew Another 55.8% in March, Overtaking Bing and DuckDuckGo " <https://www.similarweb.com/blog/insights/ai-news/chatgpt-bing-duckduckgo/> (accessed 29-05-2023, 2023).
- [59] S. Sezgin and N. Sevim Cirak, "The role of MOOCs in engineering education: An exploratory systematic review of peer - reviewed literature," *Computer Applications in Engineering Education*, vol. 29, no. 4, pp. 950-968, 2021.
- [60] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, 2023.
- [61] M. Javaid, A. Haleem, R. P. Singh, S. Khan, and I. H. Khan, "Unlocking the opportunities through ChatGPT Tool towards ameliorating the education system," *Benchmark Transactions on Benchmarks, Standards and Evaluations*, vol. 3, no. 2, p. 100115, 2023/06/01/ 2023, doi: <https://doi.org/10.1016/j.tbench.2023.100115>.
- [62] N. Koukis and A. Jimoyiannis, "MOOCS for teacher professional development: exploring teachers' perceptions and achievements," *Interactive Technology and Smart Education*, vol. 16, no. 1, pp. 74-91, 2019.

- [63] S. Iqbal, X. Zang, Y. Zhu, Y. Y. Chen, and J. Zhao, "On the impact of MOOCs on engineering education," in *2014 IEEE International Conference on MOOC, Innovation and Technology in Education (MITE)*, 2014: IEEE, pp. 101-104.
- [64] T. N. Hopfenbeck, "The Future of Educational Assessment: Self-assessment, Grit and ChatGPT?," *Assessment in Education: Principles, Policy & Practice*, vol. 30, no. 2, pp. 99-103, 2023/03/04 2023, doi: 10.1080/0969594X.2023.2212192.
- [65] E. A. Van Dis, J. Bollen, W. Zuidema, R. van Rooij, and C. L. Bockting, "ChatGPT: five priorities for research," *Nature*, vol. 614, no. 7947, pp. 224-226, 2023.
- [66] H. H. Thorp, "ChatGPT is fun, but not an author," vol. 379, ed: American Association for the Advancement of Science, 2023, pp. 313-313.
- [67] P. Hacker, A. Engel, and M. Mauer, "Regulating ChatGPT and other large generative AI models," in *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, 2023, pp. 1112-1123.
- [68] R. Peres, M. Schreier, D. Schweidel, and A. Sorescu, "On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice," *International Journal of Research in Marketing*, vol. 40, no. 2, pp. 269-275, 2023/06/01/ 2023, doi: <https://doi.org/10.1016/j.ijresmar.2023.03.001>.
- [69] G. Albort-Morant, J. Henseler, A. Leal-Millán, and G. Cepeda-Carrión, "Mapping the field: A bibliometric analysis of green innovation," *Sustainability*, vol. 9, no. 6, p. 1011, 2017.
- [70] S. Oduro, G. Maccario, and A. De Nisco, "Green innovation: a multidomain systematic review," *European Journal of Innovation Management*, vol. 25, no. 2, pp. 567-591, 2021.
- [71] H. Tan *et al.*, "Global evolution of research on green energy and environmental technologies: A bibliometric study," *Journal of Environmental Management*, vol. 297, p. 113382, 2021.
- [72] J. A. Moral-Muñoz, E. Herrera-Viedma, A. Santisteban-Espejo, and M. J. Cobo, "Software tools for conducting bibliometric analysis in science: An up-to-date review," *Profesional de la Información*, vol. 29, no. 1, 2020.
- [73] O. Ellegaard and J. A. Wallin, "The bibliometric analysis of scholarly production: How great is the impact?," *Scientometrics*, vol. 105, pp. 1809-1831, 2015.
- [74] WOS. "Web of Science." Clarivate Analytics. <https://clarivate.com/products/scientific-and-academic-research/research-discovery-and-workflow-solutions/webofscience-platform/> (accessed).
- [75] D. de Castro e Silva Neto, O. Cruz Carlos, F. Rodrigues, and P. Silva, "Bibliometric Analysis of PPP and PFI Literature: Overview of 25 Years of Research," *Journal of Construction Engineering and Management*, vol. 142, no. 10, p. 06016002, 2016/10/01 2016, doi: 10.1061/(ASCE)CO.1943-7862.0001163.
- [76] M. Aria and C. Cuccurullo, "bibliometrix: An R-tool for comprehensive science mapping analysis," *Journal of Informetrics*, vol. 11, no. 4, pp. 959-975, 2017/11/01/ 2017, doi: <https://doi.org/10.1016/j.joi.2017.08.007>.
- [77] N. Van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *scientometrics*, vol. 84, no. 2, pp. 523-538, 2010.
- [78] W. Hariri, "Unlocking the Potential of ChatGPT: A Comprehensive Exploration of its Applications, Advantages, Limitations, and Future Directions in Natural Language Processing," *arXiv preprint arXiv:2304.02017*, 2023.
- [79] P. Martinez, M. Al-Hussein, and R. Ahmad, "A scientometric analysis and critical review of computer vision applications for construction," *Automation in Construction*, vol. 107, p. 102947, 2019.
- [80] B. Z. John Schulman, Christina Kim, Jacob Hilton, Jacob Menick, Jiayi Weng, Juan Felipe Ceron Uribe, Liam Fedus, Luke Metz, Michael Pokorny, Rapha Gontijo Lopes, Shengjia Zhao, Arun Vijayvergiya, Eric Sigler, Adam Perelman, Chelsea Voss, Mike Heaton, Joel Parish, Dave Cummings, Rajeev Nayak, Valerie Balcom, David Schnurr, Tomer Kaftan, Chris Hallacy, Nicholas Turley, Noah Deutsch, Vik Goel, Jonathan Ward, Aris Konstantinidis, Wojciech Zaremba, Long Ouyang, Leonard Bogdonoff, Joshua Gross, David Medina, Sarah Yoo, Teddy Lee, Ryan Lowe, Dan Mossing, Joost Huizinga, Roger Jiang, Carroll Wainwright, Diogo Almeida, Steph Lin, Marvin Zhang, Kai Xiao, Katarina Slama, Steven Bills, Alex Gray, Jan Leike, Jakub Pachocki, Phil Tillet, Shantanu Jain, Greg Brockman, Nick Ryder, Alex Paino, Qiming Yuan, Clemens Winter, Ben Wang, Mo Bavarian, Igor Babuschkin, Szymon Sidor, Ingmar Kanitscheider, Mikhail Pavlov, Matthias Plappert, Nik Tezak, Heewoo Jun, William Zhuk, Vitchyr Pong, Lukasz Kaiser, Jerry Tworek, Andrew Carr, Lilian Weng, Sandhini Agarwal, Karl Cobbe, Vineet Kosaraju, Alethea Power, Stanislas Polu, Jesse Han, Raul Puri, Shawn Jain, Benjamin Chess, Christian Gibson, Oleg Boiko, Emy Parparita, Amin Tootoonchian, Kyle Kosic, Christopher Hesse. "Introducing ChatGPT." OpenAI. <https://openai.com/blog/chatgpt> (accessed 2023).
- [81] Y. K. Dwivedi *et al.*, "Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy," *International Journal of Information Management*, vol. 71, p. 102642, 2023/08/01/ 2023, doi: <https://doi.org/10.1016/j.ijinfomgt.2023.102642>.
- [82] C. K. Tiwari, M. A. Bhat, S. T. Khan, R. Subramaniam, and M. A. I. Khan, "What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT," *Interactive Technology and Smart Education*, 2023.
- [83] J. V. Pavlik, "Collaborating With ChatGPT: Considering the Implications of Generative Artificial Intelligence for Journalism and Media Education," *Journalism & Mass Communication Educator*, p. 10776958221149577, 2023.
- [84] K. M. Jablonka *et al.*, "14 Examples of How LLMs Can Transform Materials Science and Chemistry: A Reflection on a Large Language Model Hackathon," *Digital Discovery*, 2023.
- [85] A. Lahat, E. Shachar, B. Avidan, Z. Shatz, B. S. Glicksberg, and E. Klang, "Evaluating the use of large language model in identifying top research questions in gastroenterology," *Scientific Reports*, vol. 13, no. 1, p. 4164, 2023/03/13 2023, doi: 10.1038/s41598-023-31412-2.
- [86] Y. Peng, J. F. Rousseau, E. H. Shortliffe, and C. Weng, "AI-generated text may have a role in evidence-based medicine," *Nature Medicine*, pp. 1-2, 2023.

- [87] B. D. Lund, T. Wang, N. R. Mannuru, B. Nie, S. Shimray, and Z. Wang, "ChatGPT and a new academic reality: Artificial Intelligence - written research papers and the ethics of the large language models in scholarly publishing," *Journal of the Association for Information Science and Technology*, vol. 74, no. 5, pp. 570-581, 2023.
- [88] S. Moore, H. A. Nguyen, N. Bier, T. Domadia, and J. Stamper, "Assessing the Quality of Student-Generated Short Answer Questions Using GPT-3," in *Educating for a New Future: Making Sense of Technology-Enhanced Learning Adoption: 17th European Conference on Technology Enhanced Learning, EC-TEL 2022, Toulouse, France, September 12–16, 2022, Proceedings*, 2022: Springer, pp. 243-257.
- [89] S. S. Biswas, "Role of chat gpt in public health," *Annals of biomedical engineering*, vol. 51, no. 5, pp. 868-869, 2023.
- [90] X. Zhai, "Chatgpt for next generation science learning," *XRDS: Crossroads, The ACM Magazine for Students*, vol. 29, no. 3, pp. 42-46, 2023.
- [91] E. R. Mollick and L. Mollick, "Using AI to implement effective teaching strategies in classrooms: Five strategies, including prompts," *Including Prompts (March 17, 2023)*, 2023.
- [92] E. Gabajiwala, P. Mehta, R. Singh, and R. Koshy, "Quiz maker: Automatic quiz generation from text using NLP," in *Futuristic Trends in Networks and Computing Technologies: Select Proceedings of Fourth International Conference on FTNCT 2021*, 2022: Springer, pp. 523-533.
- [93] C. D. Duong, D. T. Bui, H. T. Pham, and A. T. Vu, "How effort expectancy and performance expectancy interact to trigger higher education students' uses of ChatGPT for learning," *Interactive Technology and Smart Education*, no. ahead-of-print, 2023.
- [94] A. Guersenzvaig and J. Sánchez Monedero. (2023) Nobody writing and nobody reading: artificial intelligence chatbots and the science we want.
- [95] I. Solaiman and C. Dennison, "Process for adapting language models to society (palms) with values-targeted datasets," *Advances in Neural Information Processing Systems*, vol. 34, pp. 5861-5873, 2021.
- [96] L. Ouyang et al., "Training language models to follow instructions with human feedback," *Advances in Neural Information Processing Systems*, vol. 35, pp. 27730-27744, 2022.
- [97] W. H. Organization, "Ethics and governance of artificial intelligence for health: WHO guidance," 2021.
- [98] M. Salah, H. Al Halbusi, and F. Abdelfattah, "May the force of text data analysis be with you: Unleashing the power of generative AI for social psychology research," *Computers in Human Behavior: Artificial Humans*, vol. 1, no. 2, p. 100006, 2023/08/01/ 2023, doi: <https://doi.org/10.1016/j.chbah.2023.100006>.
- [99] M. Perkins, "Academic Integrity considerations of AI Large Language Models in the post-pandemic era: ChatGPT and beyond," *Journal of University Teaching & Learning Practice*, vol. 20, no. 2, p. 07, 2023.
- [100] J. Gravel, M. D'Amours-Gravel, and E. Osmanliu, "Learning to fake it: limited responses and fabricated references provided by ChatGPT for medical questions," *Mayo Clinic Proceedings: Digital Health*, vol. 1, no. 3, pp. 226-234, 2023.
- [101] A. Borji, "A categorical archive of chatgpt failures," *arXiv preprint arXiv:2302.03494*, 2023.
- [102] A. K.-C. Chan, "Tackling Global Grand Challenges in Our Cities," *Engineering*, vol. 2, no. 1, pp. 10-15, 2016/03/01/ 2016, doi: <https://doi.org/10.1016/J.ENG.2016.01.003>.
- [103] S. Palmer and W. Hall, "An evaluation of a project-based learning initiative in engineering education," *European journal of engineering education*, vol. 36, no. 4, pp. 357-365, 2011.
- [104] K. Edström and A. Kolmos, "PBL and CDIO: complementary models for engineering education development," *European Journal of Engineering Education*, vol. 39, no. 5, pp. 539-555, 2014.
- [105] K. Tshai, J.-H. Ho, E. Yap, and H. Ng, "Outcome-based education—the assessment of programme educational objectives for an engineering undergraduate degree," *Engineering Education*, vol. 9, no. 1, pp. 74-85, 2014.
- [106] L. M. Sánchez-Ruiz, S. Moll-López, A. Nuñez-Pérez, J. A. Moraño-Fernández, and E. Vega-Fleitas, "ChatGPT Challenges Blended Learning Methodologies in Engineering Education: A Case Study in Mathematics," *Applied Sciences*, vol. 13, no. 10, p. 6039, 2023.
- [107] C. G. P. Berdanier and M. Alley, "We still need to teach engineers to write in the era of ChatGPT," *Journal of Engineering Education*, vol. 112, no. 3, pp. 583-586, 2023, doi: <https://doi.org/10.1002/jee.20541>.
- [108] J. P. Carvallo and L. Erazo-Garzón, "On the Use of ChatGPT to Support Requirements Engineering Teaching and Learning Process," in *Latin American Conference on Learning Technologies*, 2023: Springer, pp. 328-342.
- [109] C. C. L. Kwan, "Exploring ChatGPT-Generated Assessment Scripts of Probability and Engineering Statistics from Bloom's Taxonomy," in *International Conference on Technology in Education*, 2023: Springer, pp. 275-286.
- [110] M. Frenkel and H. Emara, "ChatGPT & Mechanical Engineering: Examining performance on the FE Mechanical Engineering and Undergraduate Exams," *arXiv preprint arXiv:2309.15866*, 2023.
- [111] J. Flegg, D. Mallet, and M. Lupton, "Students' perceptions of the relevance of mathematics in engineering," *International Journal of Mathematical Education in Science and Technology*, vol. 43, no. 6, pp. 717-732, 2012.
- [112] S. Sazhin, "Teaching mathematics to engineering students," *International Journal of Engineering Education*, vol. 14, no. 2, pp. 145-152, 1998.
- [113] C. Care, *Technology for modelling: electrical analogies, engineering practice, and the development of analogue computing*. Springer Science & Business Media, 2010.
- [114] B. Hodge and W. G. Steele, "A survey of computational paradigms in undergraduate mechanical engineering education," *Journal of Engineering Education*, vol. 91, no. 4, pp. 415-417, 2002.
- [115] S. A. Sorby et al., "Modernization of the mechanical engineering curriculum and guidelines for computer - aided engineering instruction," *Computer Applications in Engineering Education*, vol. 7, no. 4, pp. 252-260, 1999.
- [116] G. M. Michko, "Meta-analysis of effectiveness of technology use in undergraduate engineering education," in *2008 38th Annual Frontiers in Education Conference*, 2008: IEEE, pp. S1A-1-S1A-6.

- [117] A. Thurzo, M. Strunga, R. Urban, J. Surovková, and K. I. Afrashtehfar, "Impact of artificial intelligence on dental education: a review and guide for curriculum update," *Education Sciences*, vol. 13, no. 2, p. 150, 2023.
- [118] P. Necesal and J. Pospíšil, "Experience with teaching mathematics for engineers with the aid of Wolfram Alpha," in *Proceedings of the World Congress on Engineering and Computer Science*, 2012, vol. 1, pp. 271-274.
- [119] D. Ibrahim, "Engineering simulation with MATLAB: improving teaching and learning effectiveness," *Procedia Computer Science*, vol. 3, pp. 853-858, 2011.
- [120] A. Ozkan and K. Yildirim, "Comparison of conventional and computer-aided drafting methods from the view of time and drafting quality," *Eurasian Journal of Educational Research*, vol. 16, no. 62, 2016.
- [121] A. Zhavoronkov, "Caution with AI-generated content in biomedicine," *Nature medicine*, vol. 29, no. 3, p. 532, 2023.
- [122] P. Black and D. Wiliam, "Assessment and classroom learning," *Assessment in education*, vol. 5, no. 1, pp. 7-74, 1998.
- [123] M. Henderson, T. Ryan, and M. Phillips, "The challenges of feedback in higher education," *Assessment & Evaluation in Higher Education*, vol. 44, no. 8, pp. 1237-1252, 2019.
- [124] S. J. Deeley, "Using technology to facilitate effective assessment for learning and feedback in higher education," *Assessment & Evaluation in Higher Education*, vol. 43, no. 3, pp. 439-448, 2018/04/03 2018, doi: 10.1080/02602938.2017.1356906.
- [125] Y. Chen, S. Jensen, L. J. Albert, S. Gupta, and T. Lee, "Artificial intelligence (AI) student assistants in the classroom: Designing chatbots to support student success," *Information Systems Frontiers*, vol. 25, no. 1, pp. 161-182, 2023.
- [126] E. R. Mollick and L. Mollick, "New modes of learning enabled by ai chatbots: Three methods and assignments," *Available at SSRN*, 2022.
- [127] R. L. Norton, *Machine design*. Prentice Hall, 2010.
- [128] I. Van Kesteren, "Product designers' information needs in materials selection," *Materials & Design*, vol. 29, no. 1, pp. 133-145, 2008.
- [129] I. E. H. van Kesteren, "Product designers' information needs in materials selection," *Materials & Design*, vol. 29, no. 1, pp. 133-145, 2008/01/01/ 2008, doi: <https://doi.org/10.1016/j.matdes.2006.11.008>.
- [130] P. S. Ramalhet, A. M. R. Senos, and C. Aguiar, "Digital tools for material selection in product design," *Materials & Design (1980-2015)*, vol. 31, no. 5, pp. 2275-2287, 2010/05/01/ 2010, doi: <https://doi.org/10.1016/j.matdes.2009.12.013>.
- [131] F. Akın and O. Pedgley, "Sample libraries to expedite materials experience for design: A survey of global provision," *Materials & Design*, vol. 90, pp. 1207-1217, 2016/01/15/ 2016, doi: <https://doi.org/10.1016/j.matdes.2015.04.045>.
- [132] Authentise, "3DGPT," ed: Authentise, 2023.
- [133] S. Tech, "Meet the SprutCAM X AI assistant," ed: SprutCAM Tech, 2023.
- [134] S. Badini, S. Regondi, E. Frontoni, and R. Pugliese, "Assessing the capabilities of ChatGPT to improve additive manufacturing troubleshooting," *Advanced Industrial and Engineering Polymer Research*, vol. 6, no. 3, pp. 278-287, 2023/07/01/ 2023, doi: <https://doi.org/10.1016/j.aiepr.2023.03.003>.
- [135] D. A. Leonarcl, P. Branchs, and A. Eolmonofson, "Virtual teams: Using communications technology to manage geographically dispersed development groups," *Managing Knowledge Assets, Creativity and Innovation*, vol. 325, 2011.
- [136] M. E. Sosa, S. D. Eppinger, M. Pich, D. G. McKendrick, and S. K. Stout, "Factors that influence technical communication in distributed product development: an empirical study in the telecommunications industry," *IEEE transactions on engineering management*, vol. 49, no. 1, pp. 45-58, 2002.
- [137] M. Tolouei-Rad, "An approach towards fully integration of CAD and CAM technologies," *Journal of achievements in materials and manufacturing engineering*, vol. 18, no. 1-2, pp. 31-36, 2006.
- [138] B. S. Dhillon, *Creativity for engineers*. World scientific, 2006.
- [139] G. Cooper, "Examining science education in chatgpt: An exploratory study of generative artificial intelligence," *Journal of Science Education and Technology*, vol. 32, no. 3, pp. 444-452, 2023.
- [140] T. J. Allen, D. M. Lee, and M. L. Tushman, "R&D performance as a function of internal communication, project management, and the nature of the work," *IEEE Transactions on engineering management*, no. 1, pp. 2-12, 1980.
- [141] W. F. Wiggins and A. S. Tejani, "On the opportunities and risks of foundation models for natural language processing in radiology," *Radiology: Artificial Intelligence*, vol. 4, no. 4, p. e220119, 2022.
- [142] A. J. Thirunavukarasu, D. S. J. Ting, K. Elangovan, L. Gutierrez, T. F. Tan, and D. S. W. Ting, "Large language models in medicine," *Nature Medicine*, pp. 1-11, 2023.
- [143] S. Brainard and Z. Szajnfarber, "Understanding the burden of government oversight on engineering work: Adding empirical data to the debate," *Space Policy*, vol. 42, pp. 70-80, 2017.
- [144] J. Bird and C. Ross, *Mechanical engineering principles*. Routledge, 2014.
- [145] S. Mishra *et al.*, "Numglue: A suite of fundamental yet challenging mathematical reasoning tasks," *arXiv preprint arXiv:2204.05660*, 2022.
- [146] Z. Chu *et al.*, "A survey of chain of thought reasoning: Advances, frontiers and future," *arXiv preprint arXiv:2309.15402*, 2023.
- [147] S. Frieder *et al.*, "Mathematical capabilities of chatgpt," *arXiv preprint arXiv:2301.13867*, 2023.
- [148] S. Chong, G.-T. Pan, J. Chin, P. L. Show, T. C. K. Yang, and C.-M. Huang, "Integration of 3D Printing and Industry 4.0 into Engineering Teaching," *Sustainability*, vol. 10, no. 11, p. 3960, 2018. [Online]. Available: <https://www.mdpi.com/2071-1050/10/11/3960>.
- [149] M. Baechle-Clayton, E. Loos, M. Taheri, and H. Taheri, "Failures and flaws in fused deposition modeling (FDM) additively manufactured polymers and composites," *Journal of Composites Science*, vol. 6, no. 7, p. 202, 2022.
- [150] C. Klahn and M. Meboldt, *Industrializing Additive Manufacturing - Proceedings of AMPA2020*. 2020.