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

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Abstract

Purpose: Following the recent rise in generative artificial intelligence (GenAI) tools, fundamental questions about their wider impacts have started to reverberate around various disciplines. Despite attempts to address these questions in prior work, there are still subfactors specific to different disciplines that need to be untangled. To this end, this study sets out as a narrative inquiry to examine the implications of GenAI tools for mechanical engineering.

Design/Methodology:

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 select GenAI tools (Bard, ChatGPT, DALL.E, and 3DGPT) for mechanical engineering-related tasks.

Findings:

The study identifies several pedagogical and professional opportunities and guidelines for deploying GenAI tools in mechanical engineering. Besides, the study uncovered some pitfalls of GenAI tools for analytical reasoning (benign errors in computation) and sketching/image generation tasks (lack of understanding of symmetry).

Originality:

To the best of the authors' knowledge, this study presents the first narrative inquiry into the potential of GenAI for the field of mechanical engineering. Specifically, it provides a unique focus on the implications of GenAI tools specifically for mechanical engineering, combining scientometric analysis, experimentation, and pedagogical insights.

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

1. Introduction

One of the relentless demands on students and educators in the 21st century is digital competency [1, 2]. Lately, the boundary of essential digital skills required to thrive in the post-industrial digital economy has been expanded by the dizzying development in generative artificial intelligence (GenAI) ecosystems. Yet, our understanding of the far-reaching pros and cons that this new chapter in AI-centric digital competency portends across various domains is only just taking shape. Dominated by the pervasive sense of the dual-use risks emanating from the rapid release of GenAI tools to the public, the discourse around large language model (LLM) has revealed that a lot is at stake. As a result, many countries, universities, and journals are now pushed to devise rules of engagement or rules for accountability for their use [3-5]. Ultimately, the policy landscape remains in flux. Notwithstanding, the question about the consequential influence of GenAI tools on various aspects of the education industry and academia has undoubtedly taken centre stage [6, 7].

In this vein, this paper attempts to cast a spotlight on the possible consequential implications of this development for Mechanical Engineering. Primarily, building on a string of recent studies and commentaries in this area [8-13], the current paper echoes the need for universities to confront the hard question of what to do with these tools and further engages with the uncovering of the potential of these tools to serve as part of the broader instruments for enhancing engineering education and professional practices. Concretely, the motivation for the study is to explore the implication of these tools for the field of mechanical engineering.

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 highlights the gap in the literature.
- **Section 3** highlights the gap in the literature, hints at the parallel between GenAI tools and MOOC, and introduces a brief bibliometric analysis of the published studies to sieve through the trend of the academic discourse on the subject matter.
- **Section 4** discusses the implication of GenAI tools for mechanical engineering education, critically discussing specific domain applications, challenges, and guidelines along with a presentation of experiments of select GenAI tools for mechanical engineering-related tasks.

2. From stochastic parrots to intelligent machines

In the most basic form, GenAI encompasses the wide range of AI tools that have lately become popular for content creation using textual or natural language queries called "prompt". Many of these tools are heralded by development in LLMs, an outgrowth of natural language processing (NLP), which itself represents a strand of machine learning (ML) techniques [14].

Interestingly, language model – a term that refers to an unsupervised ML system trained on a string of prediction tasks [15], is historically a decades-old idea envisioned in the 1949 seminal work of Shannon [16]. Due to constraints, earlier implementations of language models were largely restricted in scope. They were mostly utilized for machine translation and automatic speech recognition [15]. Indeed, as recent as 2021, LLMs were regarded as "stochastic parrots", a metaphor coined by Bender, et al. [17] to connote that LLMs are probabilistic statistical models merely repeating the texts on which they are trained with no inherent understanding of the world. 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 [18, 19].

Developed in the form of conversational agents or AI assistants, 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. [20, 21]. However, beyond textual information generation, these tools have also achieved remarkable progress with the generation of simple to advanced artistically-constructed images, animations, audio, videos, audio-video contents such as films, etc [22]. Functionally, the capacity of these applications is driven in large part by the quartet of the large corpus of big data in the form of web text, enhanced computer hardware, high-capacity models with hundreds of millions/billions of parameters, and state-of-the-art training architecture premised on the Transformer-based Deep Neural Network (DNN) [23-26]. 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

Year of Release	*Model*	*# Parameters*	*Company*
2023	GPT-4	~100 trillion	OpenAI
2023	PaLM-2 [27]	540 billion	Google
2023	LLaMA-1 [28]	65 billion	Meta
2023	LLaMA-2 [28]	70 billion	Meta
2022	ChatGPT	20 billion	OpenAI
2022	BLOOM [29]	176 billion	BigScience
2021	Megatron-Turing NLG	530 billion	Nvidia/Microsoft
2020	GPT-3 [30]	175 billion	OpenAI

Meanwhile, in contrast with the traditional machine learning models, LLMs are generally task-agnostic [31-34]. Consequently, they are endowed with various fascinating and unexpected emergent behaviours that are not hard-coded during the training process [30, 35]. This 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 them as "foundational models" [24], even if questions remain about their "universal competency" [36].

Presently, most foundation models or LLMs are owned by large corporations as revealed in Table 1. 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, 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 [37-41], utilitarian dimensions covering drug discovery [42], ethical use in scientific research [43, 44], alignment with human value [45], to adversarial misuse [46, 47], among others.

Table 2: A select 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
Translation	DeepL, Reverso Context
3D printing	3DGPT

3. The impact of 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 expansive body of literature dissecting issues around ChatGPT by building on studies by Lo [8], Nikolic, et al. [48], Pursnani, et al. [49], Menekse [50], Gill, et al. [51], among others.

However, many of the existing studies have largely touched on the implications of ChatGPT and GenAI tools for general education, and much less from the angle of engineering education as will be shown in subsection 3.3. In contrast, this paper embarks on examining the implications of these tools with a focus on the nuances of their utility for the field of mechanical engineering. Besides, as mentioned by Eke [22], 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 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/questions of relevance to the field of mechanical engineering.

To begin the analysis, the next subsections that follow synthesized the implications of these tools on education. Subsection 3.2 emphasizes the parallel between the popularity of GenAI tools and Massive Online Open Courses (MOOC), subsection 3.3 presents the outcome of the bibliometric analysis of published studies, and subsection 3.4 distils the emerging 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 [52]. Similarly, the growth of MOOCs and GenAI is driven largely by the wide availability of computing devices and network effects [53]. 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 [54]. 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 [55-57]. 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 [56].

Nonetheless, while MOOCs focused predominantly on content delivery, GenAI tools are geared primarily towards content generation. Moreover, whereas MOOC is often favourably viewed as a revolutionary technology that altered the economies of education [58], GenAI tools such as ChatGPT have elicited a mixture of emotions [59]. For this reason, palpable concerns about these tools have led to some journal editorials forbidding a 1:1 use of contents from LLM-powered GenAI tools in manuscripts [4, 60].

3.3 Bibliographic 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 primarily offers a powerful framework for network analysis of knowledge domains as highlighted by Albort-Morant, et al. [61]. 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 [62-65]. Meanwhile, 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.

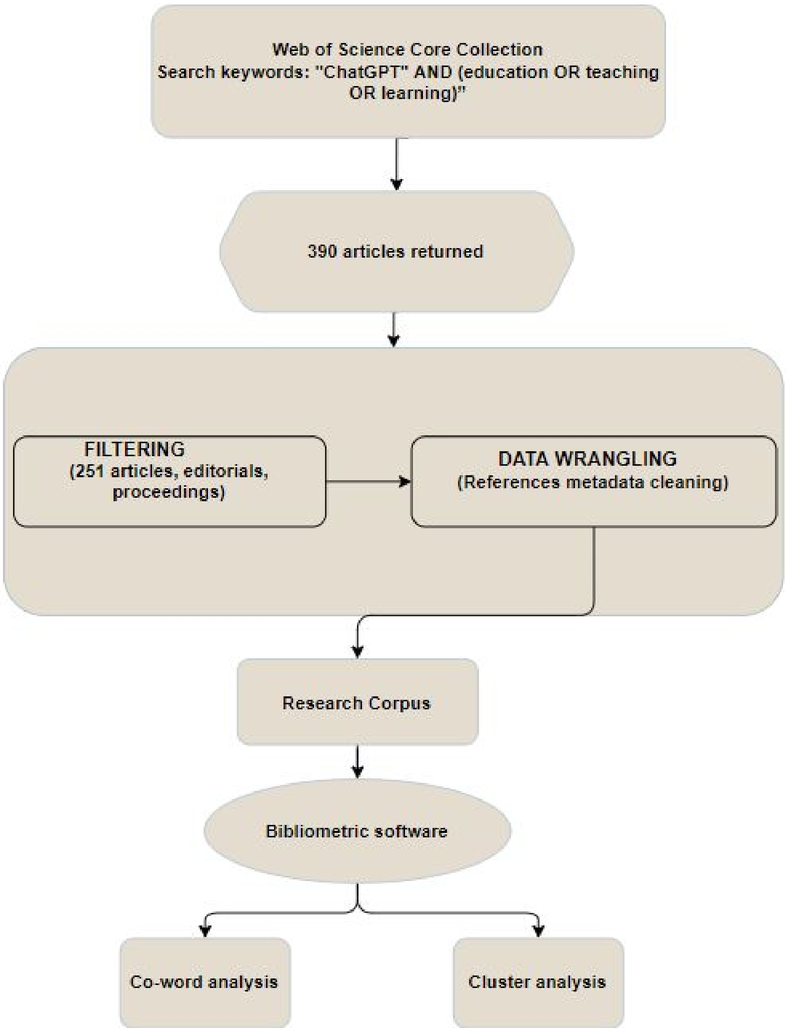


Figure 1: Literature search for scientometric analysis

As the figure shows, the search of the bibliographic records was conducted within the database of the Clarivate Analytics Web of Science [66], which is known to contain a wide coverage of reliable research articles [67]. 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 VOS [68, 69].

Figure 2 highlights the top 25 subject areas with at least five publications each, 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 [70].

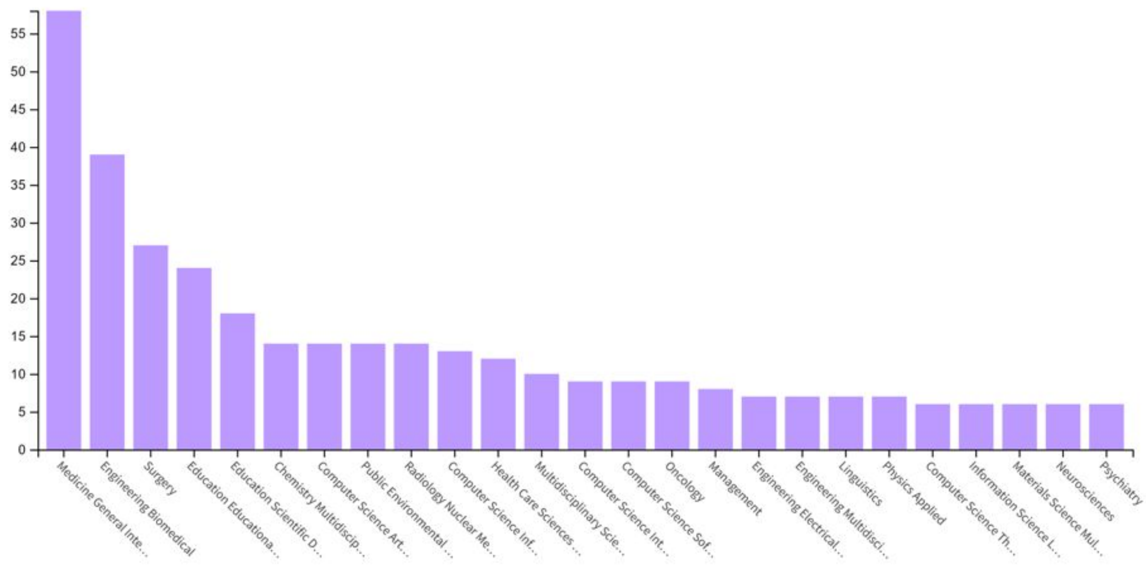


Figure 2: Distribution of the top 25 fields (with at least 5 articles)

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 [71]. 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, it must occur at least 5 times within the aggregated published studies (this is known as a *minimum number of occurrences*). 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.

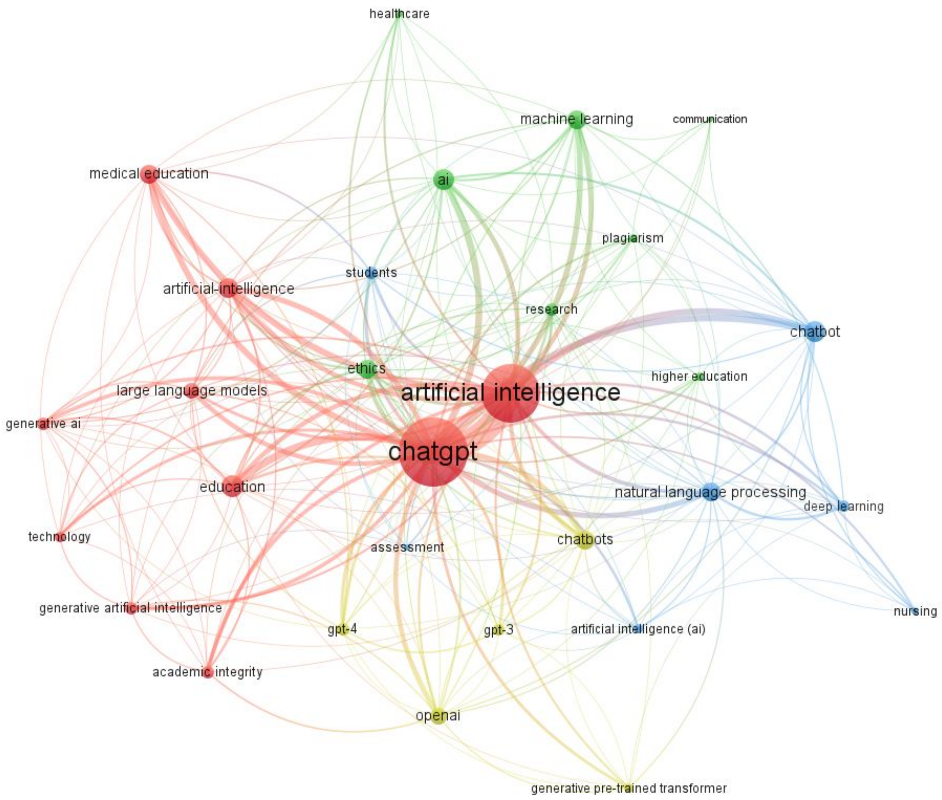


Figure 3: Network of related keywords in published studies on ChatGPT/GenAI and education. Each node in the network map identifies occurring at least 4 times and the size of the node is proportional to the number of occurrences of that term.

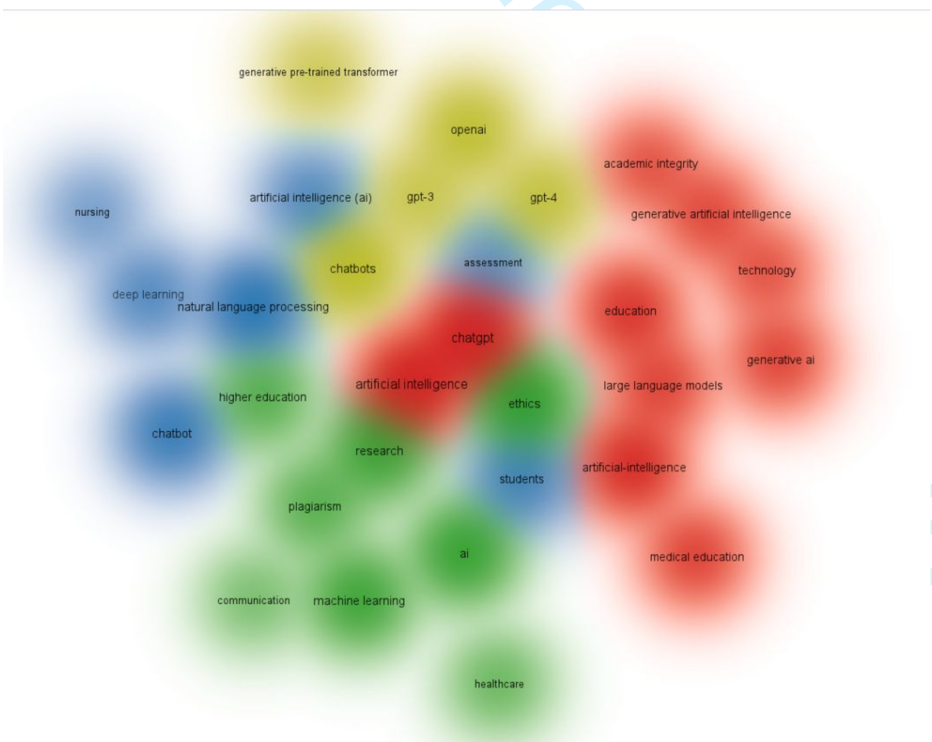


Figure 4: Cluster map of sub-domains in the published studies on GenAI and education

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
AI	56
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 Emerging perspectives on ChatGPT/GenAI for education

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 in November 2022 of ChatGPT [72].

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. [20] and Dwivedi, et al. [73]. These two studies present rigorous transdisciplinary exploratory perspectives that wrestled with fundamental questions that border on the pedagogical, operational, and ethical usage of GenAI tools on the larger educational landscape. Concretely, Kasneci, et al. [20] 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. [73], 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).

More recently, the work by Farrokhnia, et al. [10] invoked the SWOT analysis framework to offer insight into the strengths/opportunities and weaknesses/threats of ChatGPT. Other studies are more discipline-specific. For instance, Pavlik [74] reflected on the capacity and limitations of ChatGPT for journalism and media education. Jablonka, et al. [75] presented concrete examples of how GenAI tools can be used to transform material science. Lahat, et al. [76] showcased how GenAI tools can be used to identify top research areas in gastroenterology, Peng, et al. [77] highlighted its use for evidence-based medicine, while Lund, et al. [78] discussed the benefit of using ChatGPT for scholarly publishing. The work by Moore, et al. [79] and Biswas [80] explored applications in chemistry education and public health, respectively. Put together, the above studies have identified several obvious and unintended implications of these 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 [9, 11, 73, 75, 81-85]

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

3.4.2 Ethical issues, risks, and challenges

As reflected in the bibliometric analysis of the preceding section, key fundamental virtues of academia that seemed poised to be challenged by these tools are academic integrity and assessment. But as already highlighted by Van Dis, et al. [3] and Guersenzvaig and Sánchez Monedero [86], the use of various GenAI tools, as they keep increasing in maturity, sophistication and quality, is inevitable. Yet, despite the astonishing progress in the development of LLM-powered tools such as ChatGPT, much of the GenAI technology is still largely imperfect. Consequently, several criticisms have been put forth. Earlier criticism 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 [87-89]. Apart from this, other risks and challenges associated with conversational GenAI have started to emerge. A summary of other salient points about the threat and concerns around ChatGPT/GenAI tools are outlined below [3, 11, 20, 90, 91]:

- 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

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 [3] or simply invent facts, such as fake references [92]. Among others, Borji [93] and Hariri [70] recently presented a compilation of some of the epic failures/limitations of ChatGPT due 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 many more societal problems requiring technical solutions [94]. Tackling these challenges will often require a repertoire of competencies.

Attempts to instil some of these competencies to prepare 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 [95-97]. 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 [91]. Therefore, with the growing digitization 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. [48]. The authors reported a multi-disciplinary and multi-institutional study on the implication of ChatGPT for general engineering education assessments. Sánchez-Ruiz, et al. [98] examined the role of ChatGPT in the reinforcement of mathematical concepts. Qadir [9], Johri, et al. [13], Berdanier and Alley [99] and Menekse [12] discussed and highlighted areas of applications and 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. Interestingly, there are still a few grey areas that remain uncovered. For this reason, relative to the prior studies, this section restricts attention to mechanical engineering and contain a deep dive into the applications of the field for mechanical engineering education and professional practices.

4.1 GenAI-infused teaching in mechanical engineering education

There is a tight connection between number crunching and the engineering field [100]. 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 [101]. 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.) [102, 103]. 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 [104], leading to an active area of research [105].

Understandably, there are still palpable concerns about GenAI tools. However, it cannot be denied that these tools have recently reached an inflection point [106], 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. [107]. 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. [108, 109]. For instance, mechanical drafting used to be a predominantly manual activity, but has now been almost completely replaced by tools like AutoCAD [110].

Nevertheless, the pedagogical utility of technologies has 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 prompts can thus be error-prone, as will be shown in subsection 4.5, and as also recently revealed by Zhavoronkov [111] for biomedicine. In other words, for the time being, reconciling the output of GenAI tools with factual engineering observations and the most current developments in research 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 tasks.

4.2 Other potential upsides of GenAI tools for mechanical engineering

4.2.1. 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 [112]. 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 [113]. Providing feedback on summative assessment has been termed *assessment of learning* [114]. 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 [112], 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 [115, 116]. With proper tailoring of such a tool for low-stake tests as proposed by Mollick and Mollick [83], 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.

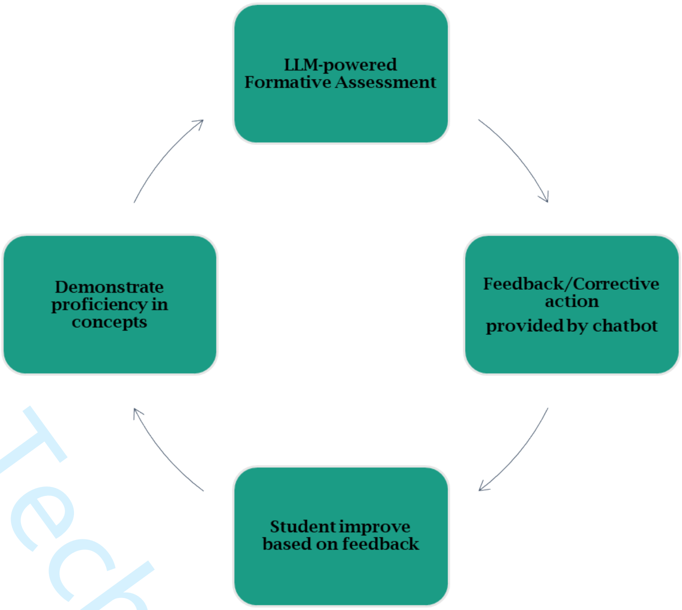


Figure 5: A proposed framework for assessment for learning

4.2.2 AI-powered search engine for material discovery and selection

Selecting appropriate 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 [117]. 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, relevant industry handbooks, etc [118, 119]. In the past simple libraries have been devised to help in this process [120], but they are often limited in scope [121]. 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.

4.2.3 AI-assisted chatbot 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 12000 journal articles and additive manufacturing standards [122]. LLM-powered applications such as 3DGPT may represent the future of decision support systems for additive manufacturing materials and processes that can be used by engineers, makers, and 3D printing enthusiasts. Another recent example is *Éncy*, developed by SprutCAM Tech [123], 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 in manufacturing. Indeed, Badini, et al. [124] 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 (FDM).

Figure 6: 3DGPT interface

4.2.4 AI-augmented technical documentation development

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 [125]. 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. [126]. In this regard, the integration of 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 renewable energy 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 [7].

4.2.5 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 [127]. Nonetheless, these tools are meant to cater only partially for the intermediate stages of the design process (product structural analysis, virtual prototyping, 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 [128]. 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. 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 the product 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, a common mistake is found to be a lack of symmetry. For instance, the front tires in Figure 8(a) are unequal. Two obvious errors (a technically inaccurate tire and a missing tire) are indicated in Figure 8(b). 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 technical descriptions and uncovering relevant concepts from prior art.

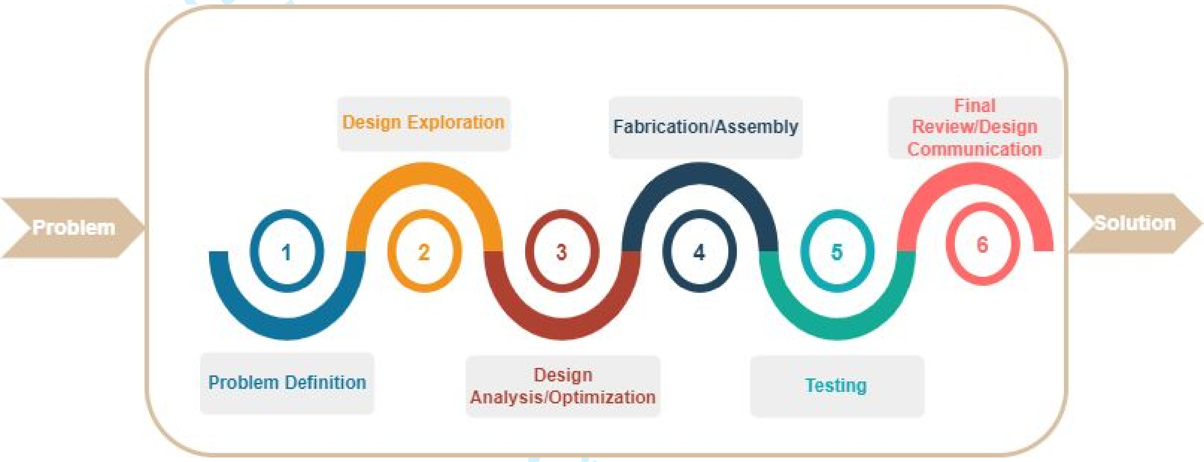
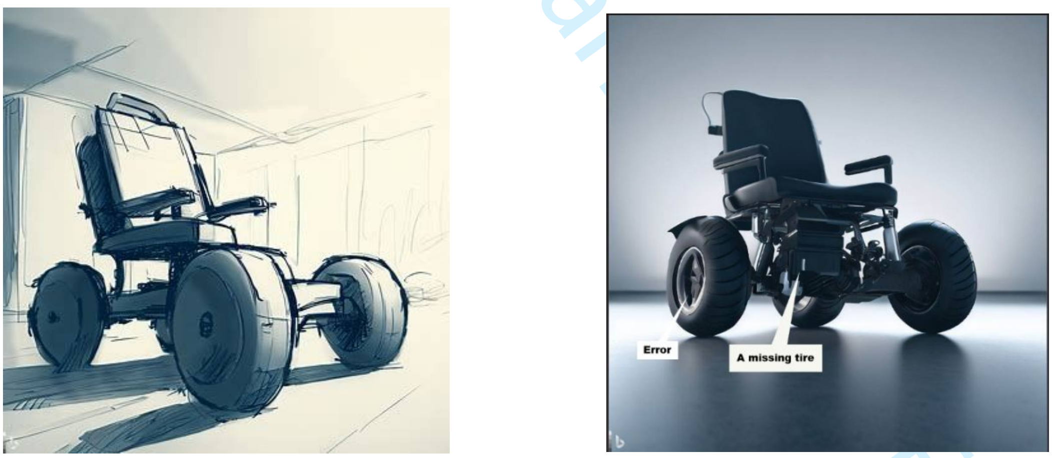


Figure 7: Engineering design process



(a) (b)

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

4.3 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. 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.
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 a misinterpretation of abbreviations or specific terminology.
Oversimplification	GenAI tools may oversimplify complex engineering concepts, omit important details, or fail to capture the intricacies of real-world mechanical systems.
Validation of outputs	GenAI-generated solutions should be validated through appropriate engineering methods. 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 [22]. Hence, it is imperative that GenAI-generated images must be carefully examined to avoid copyright violations.
Uncertainty handling in complex system design	GenAI tools might not adequately 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 and code of practices, etc.

4.4 Developing guidelines for ethical deployment of generative AI tools

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 [9], and others [129]. Nonetheless, in light of the possible risks associated with these tools, a few inexhaustive guidelines to ensure the ethical deployment of generative AI in this field 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 [130], ranging from research, development and service tasks, clear policies on when and how GenAI tools can be used must be implemented. In other words, engineering companies, similar to other industries [24, 131, 132], will have to institute clear communication and policy on GenAI's role, capabilities, and limitations.

Second, oversight (both ethical and regulatory) has always been a crucial socio-technical pillar of the traditional engineering project management framework [133]. 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 project objectives, industry standards and regulatory concerns. Third, professional engineers/engineering students will have to ensure that GenAI-generated solutions adhere to ethical/safety standards and the deployment complies with industry regulations. Finally, efforts must be directed towards the protection of sensitive data shared with the GenAI system and regularly assess/address biases in training data and outputs.

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

This section details a brief demonstration of a few capabilities of the GenAI tools listed in Table 5. The first two tools are considered general-purpose text-based GenAI systems. The third is a domain-specific GenAI tool, while the last is an image generator. Even though ChatGPT has been heavily studied in some past studies, to the best of our knowledge, none of the past studies has focused on the specific tasks we evaluated in this section.

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

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

Ultimately, Bard and ChatGPT were evaluated for their ability to solve 5 questions that can be mapped to Year 1 of the Mechanical Engineering degree as taken from [134]. It is worth noting that many more prompts were tried, but for space constraints, the responses to these 5 questions are provided here for Bard and ChatGPT. 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 [135]. Also, for transparency's sake, the version of ChatGPT employed here is with GPT3.5 as the backbone LLM (i.e., ChatGPT-3.5). While it 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.

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

Table 6 lists the prompts employed for the analytical evaluations. These questions were inspired by those in the text by Bird and Ross [134]. For each of the prompts, we zeroed in on errors generated by the tools.

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 the two applications 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 error.

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

Table 6) and a good understanding of the application of fundamental principles in fluid mechanics (prompt 5 in Put together, the outcome of the experimentations reported here revealed the growing capabilities of these GenAI tools, despite the few weaknesses highlighted. It is expected that these tools will experience sustained development and integrating them into mechanical engineering professional practices and workflow may be inevitable in response to the shift in the digital transformation induced by these tools.

Table 6). The outputs from the two applications for prompt 4 are depicted in Figure 15 and Figure 16, respectively. Meanwhile, the corresponding responses for prompt 5 are shown in Figure 17 and Figure 18, respectively. For these prompts, ChatGPT was able to determine the correct answer. 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 $v = 24.3\ m/s$ 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 [136].

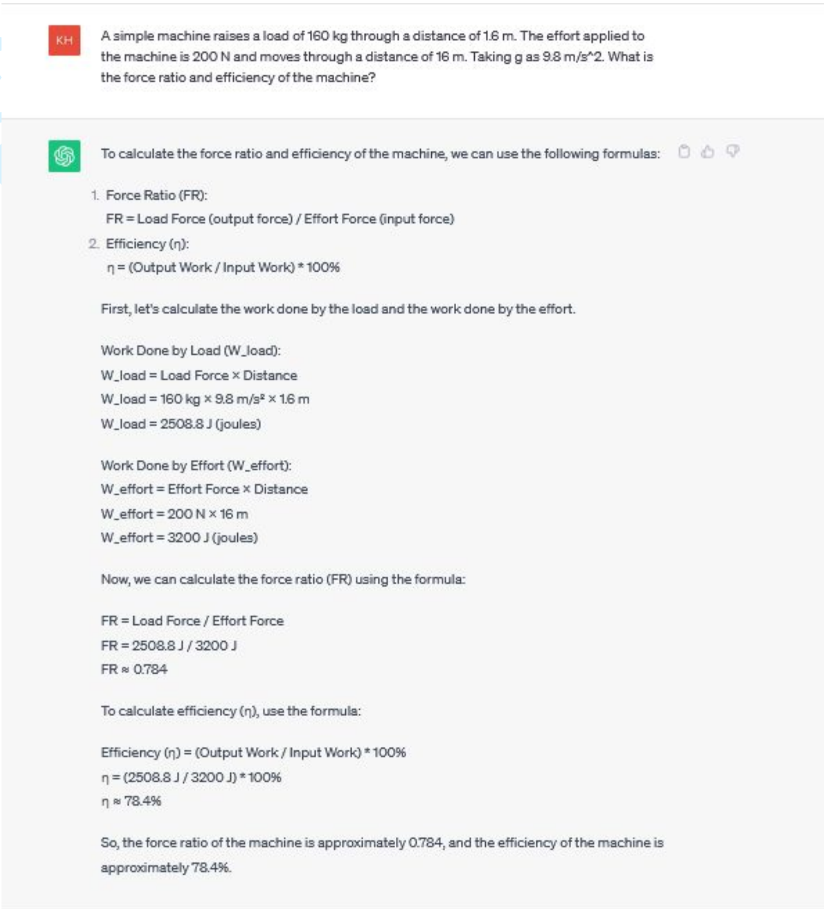
Moving on, we test 3DGPT [122], a very recent domain-specific LLM-powered application to troubleshoot a 3D printing problem. As is now well-known, 3D printing has become an integral part of engineering teaching of late [137]. One of the common issues requiring troubleshooting of FDM-based printers is nozzle blockage [138]. 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 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 [139]. 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.

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

Table 6: Prompts for the analytical reasoning evaluation

	Prompt	***Concept***	***Tool***	***Correctness of Answer***
P1	*A simple machine raises a load of 160 kg through a distance of 1.6 m. The effort applied to the machine is 200 N and moves through a distance of 16 m. Taking g as 9.8 m/s^2. What is the force ratio and efficiency of the machine?*	Statics	ChatGPT	Correct
			Bard	Correct
P2	*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?*	Statics	ChatGPT	Inconclusive
			Bard	Incorrect (unit conversion error in calculation)
P3	*A block of cast iron having a mass of 10 kg cools from a temperature of 150 degrees C to 50 degrees C. How much energy is lost by the cast iron? Assume the specific heat capacity of iron is 500 J/(kg degree C)*	Heat capacity	ChatGPT	Correct
			Bard	Correct
P4	*What is the heat energy needed to change 400 g of ice, initially, at -*	Thermal	ChatGPT	Correct

	20 degrees C, into steam at 120 degrees C?		Bard	Incorrect(addition error)
P5	*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.*	Fluid Mechanics	ChatGPT	Correct
			Bard	Incorrect (multiplication error)



KH A simple machine raises a load of 160 kg through a distance of 1.6 m. The effort applied to the machine is 200 N and moves through a distance of 16 m. Taking g as 9.8 m/s^2. What is the force ratio and efficiency of the machine?

To calculate the force ratio and efficiency of the machine, we can use the following formulas:

1. Force Ratio (FR):
   FR = Load Force (output force) / Effort Force (input force)
2. Efficiency (η):
   η = (Output Work / Input Work) * 100%

First, let's calculate the work done by the load and the work done by the effort.

Work Done by Load (W_load):
W_load = Load Force × Distance
W_load = 160 kg × 9.8 m/s² × 1.6 m
W_load = 2508.8 J (joules)

Work Done by Effort (W_effort):
W_effort = Effort Force × Distance
W_effort = 200 N × 16 m
W_effort = 3200 J (joules)

Now, we can calculate the force ratio (FR) using the formula:

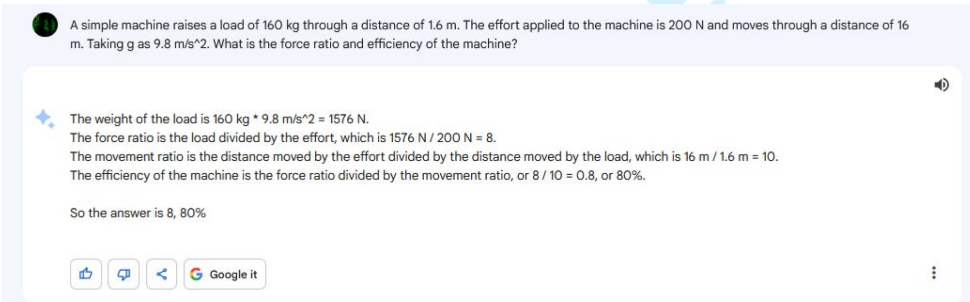
FR = Load Force / Effort Force
FR = 2508.8 J / 3200 J
FR ≈ 0.784

To calculate efficiency (η), use the formula:

Efficiency (η) = (Output Work / Input Work) * 100%
η = (2508.8 J / 3200 J) * 100%
η ≈ 78.4%

So, the force ratio of the machine is approximately 0.784, and the efficiency of the machine is approximately 78.4%.

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



A simple machine raises a load of 160 kg through a distance of 1.6 m. The effort applied to the machine is 200 N and moves through a distance of 16 m. Taking g as 9.8 m/s^2. What is the force ratio and efficiency of the machine?

The weight of the load is 160 kg * 9.8 m/s^2 = 1576 N.
The force ratio is the load divided by the effort, which is 1576 N / 200 N = 8.
The movement ratio is the distance moved by the effort divided by the distance moved by the load, which is 16 m / 1.6 m = 10.
The efficiency of the machine is the force ratio divided by the movement ratio, or 8 / 10 = 0.8, or 80%.

So the answer is 8, 80%

Google it

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

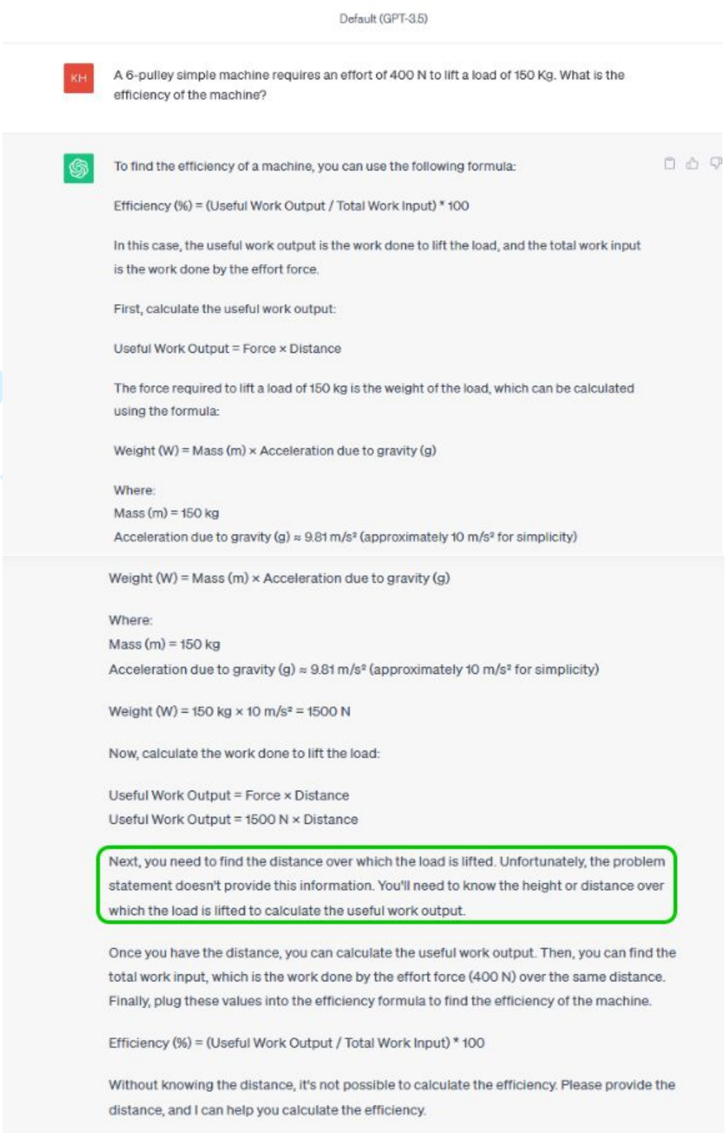


Figure 11: ChatGPT's response to a question on the efficiency of a pulley system

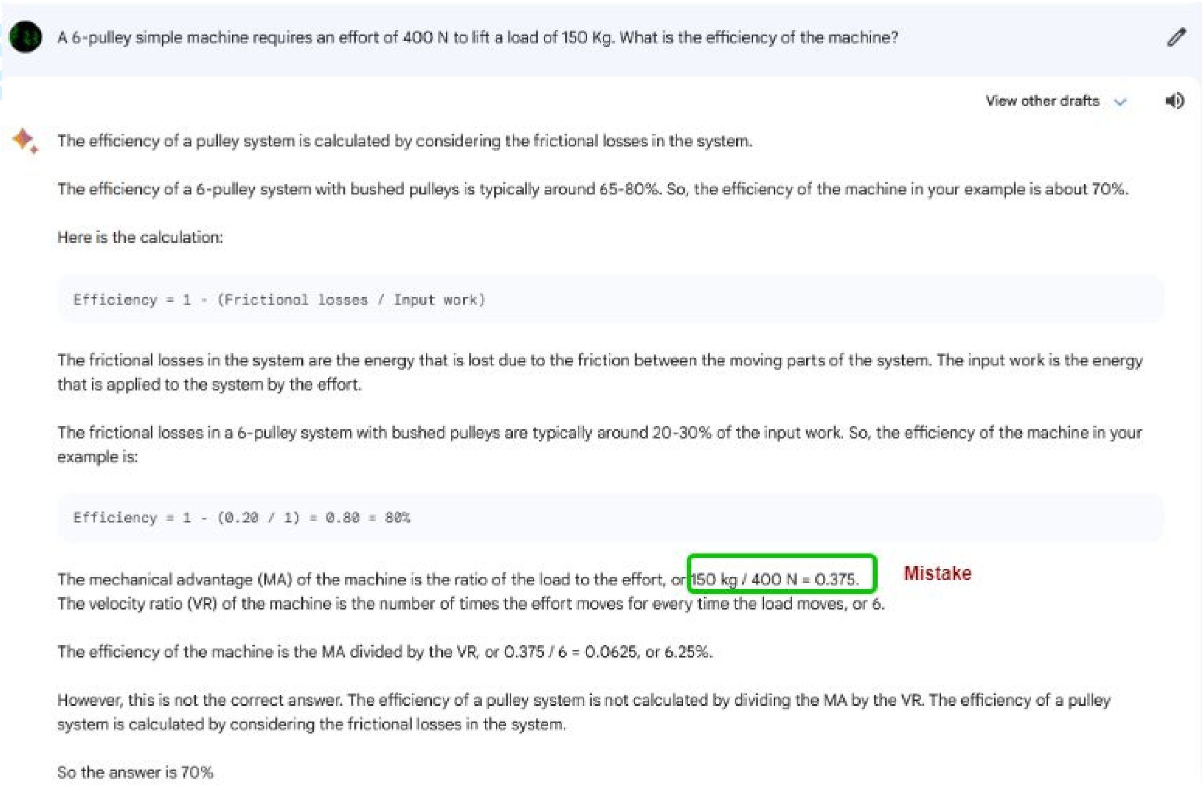
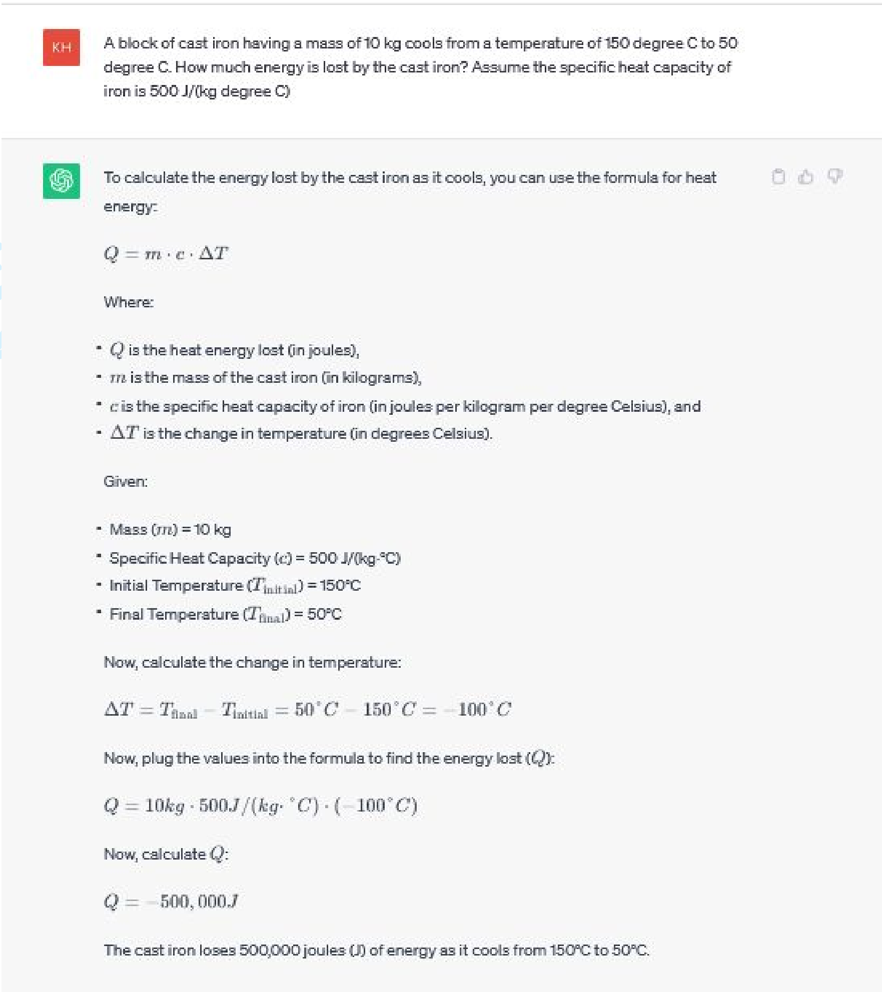


Figure 12: Bard's response to a question on the efficiency of a pulley system



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:

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

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

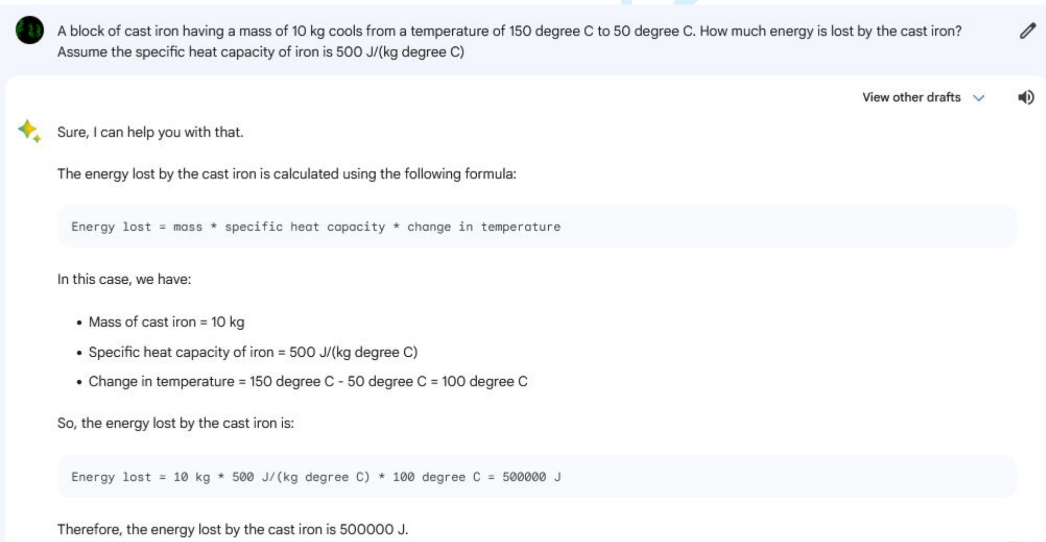
$$Q = 10kg \cdot 500J/(kg \cdot {}^{\circ}C) \cdot (-100^{\circ}C)$$

Now, calculate Q:

$$Q = -500,000J$$

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.



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)

View other drafts

Sure, I can help you with that.

The energy lost by the cast iron is calculated using the following formula:

```
Energy lost = mass * specific heat capacity * change in temperature
```

In this case, we have:

- Mass of cast iron = 10 kg
- Specific heat capacity of iron = 500 J/(kg degree C)
- Change in temperature = 150 degree C - 50 degree C = 100 degree C

So, the energy lost by the cast iron is:

```
Energy lost = 10 kg * 500 J/(kg degree C) * 100 degree C = 500000 J
```

Therefore, the energy lost by the cast iron is 500000 J.

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

KH

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:

1. 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: $Q_1 = m \cdot c_{\text{ice}} \cdot \Delta T_1$
2. 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: $Q_2 = m \cdot L_{\text{fusion}}$
3. 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: $Q_3 = m \cdot c_{\text{water}} \cdot \Delta T_3$
4. Vaporizing the water into steam at 100°C:
   - Latent heat of vaporization of water ($L_{\text{vaporization}}$) = 2,257,000 J/kg
   - Energy required for this step: $Q_4 = m \cdot L_{\text{vaporization}}$
5. 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: $Q_5 = m \cdot c_{\text{steam}} \cdot \Delta T_5$

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

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

Plug in the values for each step and calculate:

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

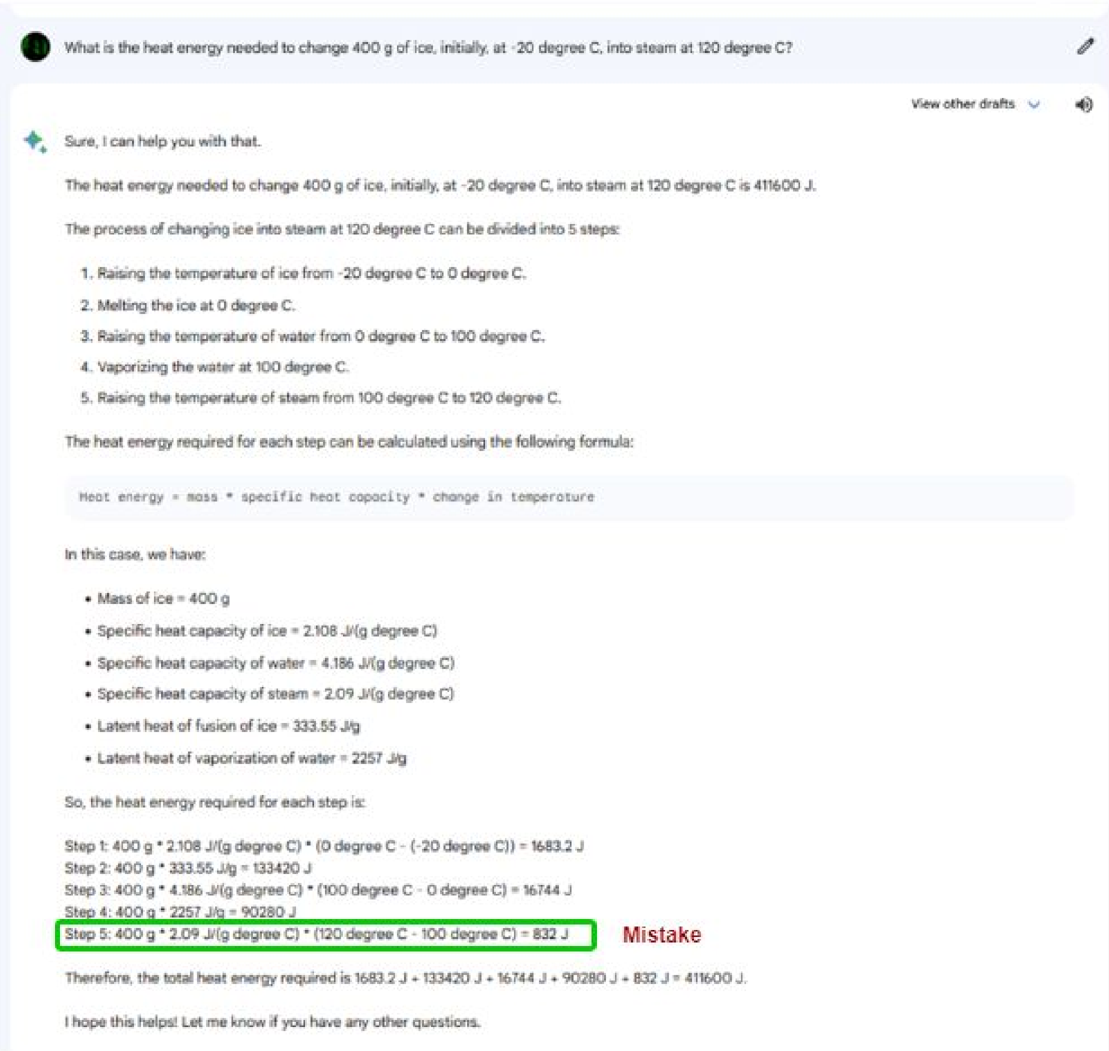
Now, calculate Q_{total}:

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

$$Q_{\text{total}} = 1121700J$$

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 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?

View other drafts

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:

```
Heat energy = mass * specific heat capacity * 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

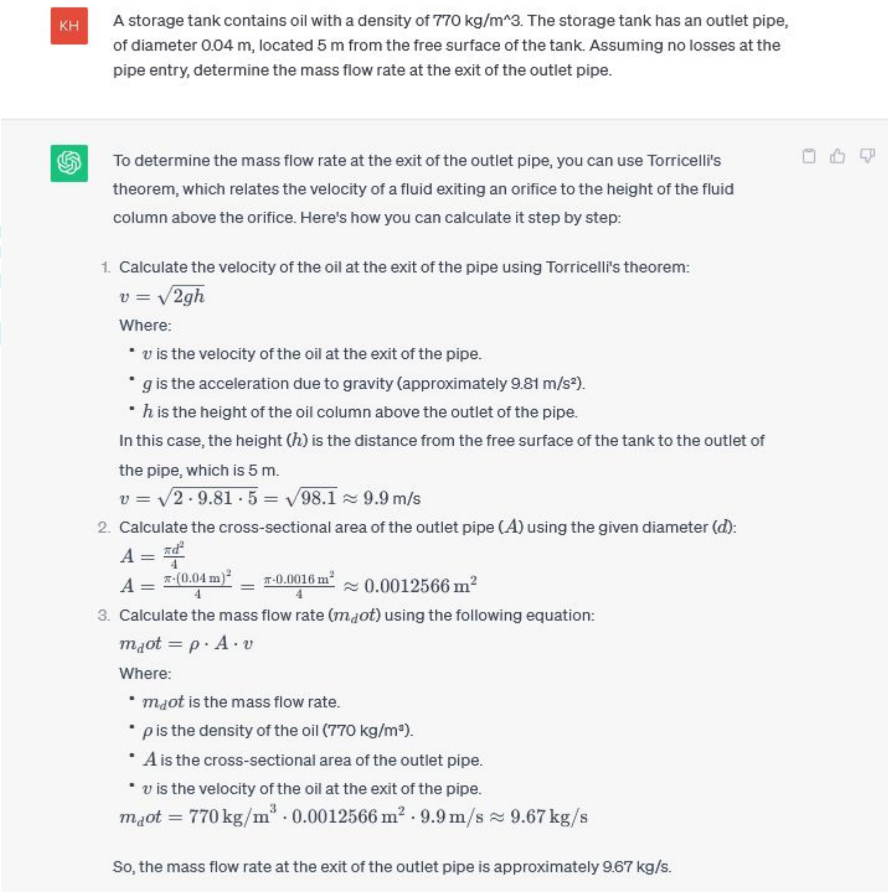
So, the heat energy required for each step is:

Step 1: 400 g * 2.108 J/(g degree C) * (0 degree C - (-20 degree C)) = 1683.2 J
Step 2: 400 g * 333.55 J/g = 133420 J
Step 3: 400 g * 4.186 J/(g degree C) * (100 degree C - 0 degree C) = 16744 J
Step 4: 400 g * 2257 J/g = 90280 J
Step 5: 400 g * 2.09 J/(g degree C) * (120 degree C - 100 degree C) = 832 J Mistake

Therefore, the total heat energy required is 1683.2 J + 133420 J + 16744 J + 90280 J + 832 J = 411600 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:

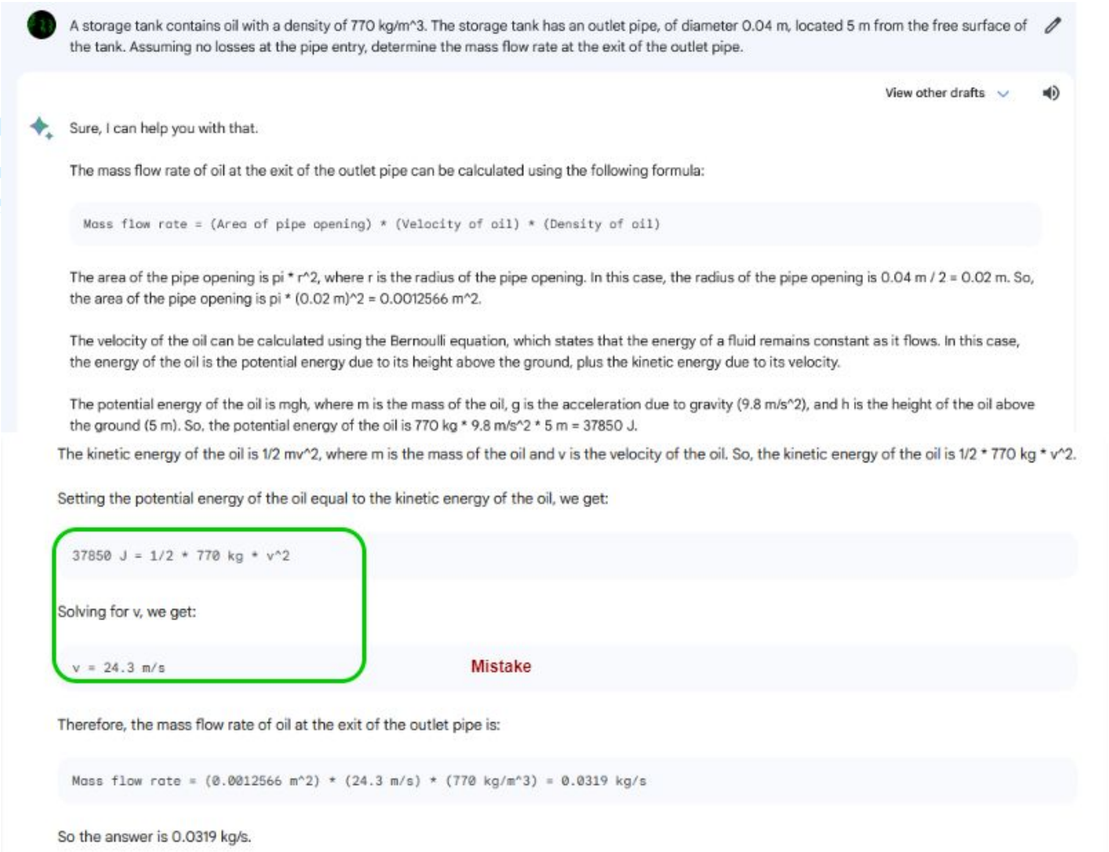
1. Calculate the velocity of the oil at the exit of the pipe using Torricelli's theorem:
   $v = \sqrt{2gh}$
   Where:
   - v is the velocity of the oil at the exit of the pipe.
   - g is the acceleration due to gravity (approximately 9.81 m/s²).
   - h is the height of the oil column above the outlet 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.
   $v = \sqrt{2 \cdot 9.81 \cdot 5} = \sqrt{98.1} \approx 9.9$ m/s
2. Calculate the cross-sectional area of the outlet pipe (A) using the given diameter (d):
   $A = \frac{\pi d^2}{4}$
   $A = \frac{\pi \cdot (0.04\,\mathrm{m})^2}{4} = \frac{\pi \cdot 0.0016\,\mathrm{m}^2}{4} \approx 0.0012566\,\mathrm{m}^2$
3. Calculate the mass flow rate ($m_d ot$) using the following equation:
   $m_d ot = \rho \cdot A \cdot v$
   Where:
   - $m_d ot$ is the mass flow rate.
   - ρ is the density of the oil (770 kg/m³).
   - A is the cross-sectional area of the outlet pipe.
   - v is the velocity of the oil at the exit of the pipe.

   $m_d ot = 770\,\mathrm{kg/m^3} \cdot 0.0012566\,\mathrm{m}^2 \cdot 9.9\,\mathrm{m/s} \approx 9.67\,\mathrm{kg/s}$

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

Figure 17: ChatGPT response to 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.

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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:

```
Mass flow rate = (Area of pipe opening) * (Velocity of oil) * (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 m / 2 = 0.02 m. So, the area of the pipe opening is pi * (0.02 m)^2 = 0.0012566 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 kg * 9.8 m/s^2 * 5 m = 37850 J.

The kinetic energy of the oil is 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 1/2 * 770 kg * v^2.

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

```
37850 J = 1/2 * 770 kg * v^2
```

Solving for v, we get:

```
v = 24.3 m/s
```

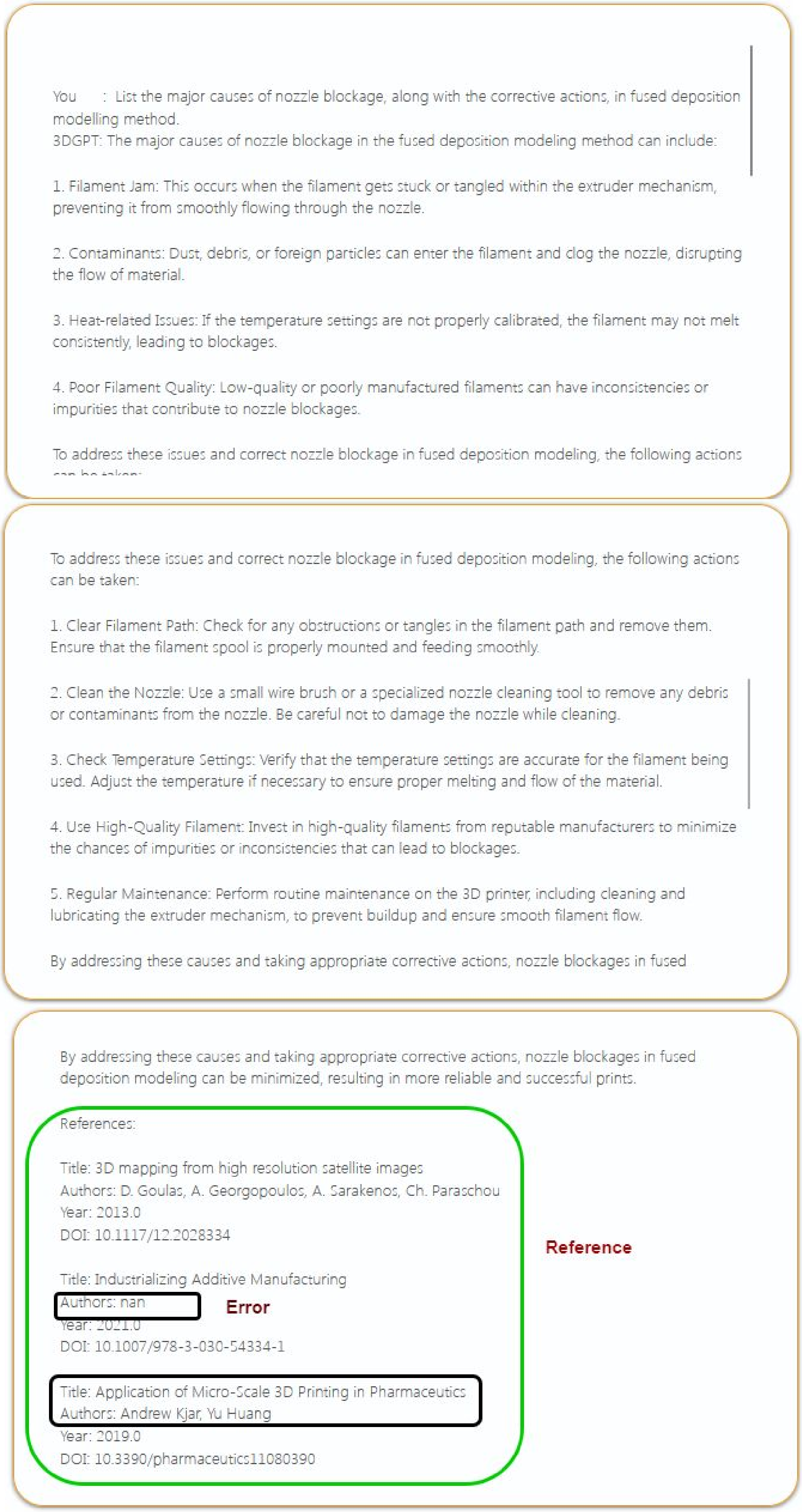
Mistake

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

```
Mass flow rate = (0.0012566 m^2) * (24.3 m/s) * (770 kg/m^3) = 0.0319 kg/s
```

So the answer is 0.0319 kg/s.

Figure 18: Bard response to 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

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.

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Authors: D. Goulas, A. Georgopoulos, A. Sarakenos, Ch. Paraschou
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DOI: 10.1117/12.2028334

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

Figure 19: 3DGPT for troubleshooting of nozzle blockage

5. Conclusion

This study has presented a short bibliometric evaluation that helped in crystallizing the emerging issues concerning ChatGPT in particular and GenAI tools in general. Beyond this, the presentation identified elements of potential applications of GenAI tools for the field of mechanical engineering, ranging from the rapid formation of formative assessment for learning and teaching to the acceleration of product development tasks such as material selection/discovery, manufacturing troubleshooting, technical documentation, and product positioning, etc. Demonstration of some of the GenAI tools with mechanical engineering-aligned prompts revealed the performance of the tools. For performance on analytical problems, both Bard and ChatGPT exhibit very strong attention to detail and present very coherent reasoning in the solution steps for all tested problems. However, they also produce errors in a few instances that boil down to an occasional lack of understanding of implicit domain knowledge and benign calculation errors involving unit conversion, addition, and multiplication. In all, the prospect of matured generative artificial intelligence (GenAI) tools is something institutions and professional societies cannot wave away. 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.

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