INTERNATIONAL DESIGN CONFERENCE – DESIGN 2024
https://doi.org/10.1017/pds.2024.202

Benchmarking AI design skills: insights from ChatGPT's participation in a prototyping hackathon

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Abstract

This study provides insights into the capabilities and performance of generative AI, specifically ChatGPT, in engineering design. ChatGPT participated in a 48-hour hackathon by instructing two participants who acted out its instructions, successfully designing and prototyping a NERF dart launcher that finished second among six teams. The paper highlights the potential and limitations of generative AI as a tool for ideation, decision-making, and optimization in engineering tasks, demonstrating the practical applicability of generating viable design solutions under real-world constraints.

Keywords: prototyping, ChatGPT, artificial intelligence (AI), engineering design

1. Introduction and background

Recent advancements in, and especially within the last year, artificial intelligence (AI) and natural language processing (NLP) have captured the attention of academia and industry due to the increase in the availability of free, easy-to-use tools such as ChatGPT and similar prompt-based generative AI tools. Multiple engineering disciplines have experimented with and adopted these tools, solving tasks such as calculations in mechanical engineering (Tiro, 2023), assessing engineering students (Qadir, 2023) as a means of fostering concept generation in product design (Filippi, 2023) and writing academic papers (Thunström, 2022). It has already started transforming the way engineers write code (Ahmad et al., 2023), and it has been used as a tool for optimising 3D printing processes (Badini et al., 2023) and to generate functional 3D models iteratively (Nelson et al., 2023). It also exhibits human-level performance on several professional and academic exams (OpenAI, 2023).
Generative design systems, initially defined by creating designs through algorithms (McCormack et al., 2004), started with a dependence on direct programming and rule-based approaches that manually encoded human design expertise (Chakrabarti et al., 2011). These systems have since evolved to utilize deep learning, driven by the expanded access to computational power. This evolution has enabled the automation of intricate tasks, including image and natural language processing (Regenwetter et al., 2022), paving the way for generative AI tools like ChatGPT.
Generative AI has transcended its traditional role as a computational aid to become a tool pervasive in most fields and will likely influence the way we conceptualize, create, refine, and design prototypes in the future. The potential for generative AI to significantly influence early-stage design processes by facilitating rapid ideation and iteration suggests that its impact will soon be felt universally across the engineering design community (Thoring et al., 2023). It has been shown to offer the potential to streamline design processes by exploring design possibilities and identifying issues (Tholander and Jonsson, 2023). Some believe Generative AI could shift engineers' focus towards the creative aspects of

their projects rather than on solving technical challenges, suggesting a transformative future for design practices (The Next Wave of Intelligent Design Automation, 2018).
Despite the growing ubiquity of generative AI in engineering disciplines, it is essential to acknowledge its limitations. Generative AI can assist in the conceptual stages of design by offering a broad understanding of principles and facilitating brainstorming (Wang et al., 2023), but it is not a universal solution. Others have reported users' scepticism regarding generative AI, specifically ChatGPT, and its ability to fully grasp the nuanced context necessary for generating innovative, high-quality designs (Tholander & Jonsson, 2023). Its use is still more prevalent in digital areas such as software and web development. At the same time, application in hardware tasks remains limited (Sajja et al., 2024) and is primarily used for idea generation (Hwang, 2022). When it comes to tasks that require exacting standards and intricate technicalities in physical realms, the performance of generative AI like ChatGPT may be inferior to that of tools tailored explicitly for such purposes. ChatGPT, for instance, trained on a wide range of licenced data, data created by human trainers and publicly available data like books, websites, and other texts spanning a wide array of subjects (OpenAI, 2023), excels at text generation, yet it may not always be the optimal choice for tasks demanding domain-specific knowledge. It is, therefore, uncertain how ChatGPT performs when asked to generate building instructions for prototypes, 3D models or mechanical solutions that often require domain-specific expertise at great accuracy and detail (Tholander and Jonsson, 2023). The optimal way to incorporate human-AI collaboration remains uncertain (Thoring et al., 2023). Further, realizing the potential of generative AI for design applications requires further testing within realistic design scenarios to close the gap between its capabilities and practical applications (Mountstephens & Teo, 2020).
Considering the advancements in generative AI and its exemplified use in various engineering applications, an intriguing inquiry emerges: How would a system like ChatGPT perform if positioned in a leading design role, tasked with ideation, decision-making, and planning in a prototyping project? This paper aims to answer that question by elucidating the implications of implementing and the performance of generative AI, specifically ChatGPT, in the early stages of engineering design by comparative analysis in a hackathon setting. The study involves ChatGPT participating in a 48-hour design hackathon, collaborating with two first-year PhD students who act as the physical executors to implement the AI's design suggestions, and comparing designs and performance to those developed by experienced engineering students. The paper reports key interactions between the human participants and ChatGPT, a description of the final design proposed by ChatGPT, and its objectively measured performance against five teams of two students. The core objective of the study is not to test whether ChatGPT is superior to graduate students in generating designs but rather to assess the extent to which generative AI can mimic or replicate the performance, creative process and problem-solving strategies employed by humans in the design process. It also highlights the practical implications of implementing ChatGPT in the design process, providing a foundation for discussing the integration of AI into the iterative design process and proposing strategies to leverage AI for enhanced productivity and innovation in engineering tasks.

2. Method

The following section delineates the approach undertaken to evaluate the application and performance of generative AI in the engineering design process. A detailed explanation of the methodology and all data files used for this research is available in a related data article (Ege et al., 2024b). However, the sections below provide a brief outline of the setup of the hackathon, the preparatory instructions for ChatGPT and human participants, the criteria for performance evaluation, and the methods employed for data collection.

2.1. TrollLabs Open Hackathon

Hackathons, as explored by Flus and Hurst (2021) and others, mirror key aspects of real-world design processes, especially in early-stage, rapid design scenarios. They are typically characterized by interdisciplinary collaboration, time constraints, agile methodologies, and provide a controlled yet authentic environment for studying design activities (Ege et al., 2024a). The hackathon conducted as part of this study occurred at TrollLabs, NTNU in Norway, a research lab focused on prototyping in the early phases of engineering design. TrollLabs has various rapid prototyping equipment and materials, including 3D printers, a laser cutter, mechatronics, CNCs, hand tools etc. In addition to the team controlled by ChatGPT, 10 participants in teams of two voluntarily signed up for the hackathon, having been invited based on their current engagement in writing their master's thesis at TrollLabs, which ensured their relevant expertise. Team ChatGPTs team members had recently finished their master's degree in mechanical engineering with a specialization in engineering design, while the other teams were in their final year of study pursuing the same degree. Participants' demographics are presented in Table 1, showing the average age of participants within each team, gender distribution, years of relevant education, and years of relevant industry work experience. Standard deviations in teams are provided in brackets. The table reveals similarities concerning age, education, and prior work experience across all teams, with a difference being Team ChatGPTs' additional year of education.

Table 1. Participant demographics

Team	Avg. age	Gender (M, F)	Education	Work experience
Team 1	23,5 (0,71)	1,1	4 (0)	2 (0)
Team 2	24,5 (0,71)	2,0	4 (0)	1 (0)
Team 3	24 (0)	2,0	4 (0)	1 (0)
Team 4	25,5 (2,12)	2,0	4 (0)	0,5 (0,71)
Team 5	23(0)	2,0	4 (0)	0,5 (0,71)
Team ChatGPT	25 (0)	2,0	5 (0)	1 (0)

The participants were unaware of the final team being instructed by ChatGPT, a measure taken to ensure unbiased behaviour and prevent any influence on the hackathon's results. The challenge spanned 48 hours, starting with the distribution of the challenge brief at the beginning of the hackathon and concluding with the testing of each team's final prototype, which was conducted outdoors immediately after the challenge period ended.

The hackathon challenge set was to make a prototype that shoots a foam NERF dart as far as possible. The prototype had to be free-standing and not connected to external power or compressed air. Teams received a new NERF dart for the final test and were not allowed to alter it in any way. They had one attempt for the final test, and the distance was measured from the end of the prototype to where the dart landed. Data capture from the hackathon includes prototype captures and the performance of prototypes. Prototypes were captured using the online app Pro2booth, a platform detailed by Giunta et al. (2022) for documenting prototyping activities by systematically recording extensive details of each prototype. The performance of each prototype in the hackathon was evaluated based on the distance it could shoot a Nerf dart. This measure provided a transparent, quantifiable means to compare each design in achieving the primary objective of the challenge. The following challenge prompt was provided to participants, and subsequently ChatGPT:

Objective:

Design and prototype a free-standing device that can fire a Nerf dart as far as possible.

Rules & Guidelines:

1. Duration: The hackathon will begin on 17th October at 10:00 am and will conclude on 19th October at 10:00 am.
2. Budget: Each participating team has a budget of 300 NOK for supplies. Receipts must be kept and presented upon request to ensure compliance.
3. Scavenging: Participants are free to scavenge parts and materials from both "Ubåten" and "TrollLabs". However, any damage to existing equipment or infrastructure during scavenging will lead to disqualification.

4. Prototype Requirements:
   a) The device must be free-standing.
   b) No external power sources or external pressurized air can be used.
   c) The device must be safe to operate. Any device deemed unsafe by the organizers will be disqualified.
5. Testing:
   a) All testing must be done in the designated "Green Room".
   b) Teams are allowed unlimited tests during the hackathon, but only one final test for the official measurement.
   c) The length will be measured from the starting point to where the rubber tip of the dart stops.

The Nerf dart's plastic tip must be whole when arriving at its goal.
For the final test, you will be provided a NEW Nerf and YOU are NOT ALLOWED TO ALTER IT IN ANY WAY OR FORM!

6. Location: All prototyping activities must be carried out within TrollLabs. Leaving the premises with the prototype or for prototyping purposes will lead to disqualification.
7. Prize: The team with the prototype that shoots the Nerf dart the farthest will win a gift card worth 1000 NOK.
8. Judging: The decision of the organizers and judges is final. Any attempts to influence or argue with the judges will lead to disqualification.

The final test:
The test starts on Thursday 19. October at 10 AM.
When testing the team will be given a completely new dart.
You only have one try on the final test.

2.2. Instructions for ChatGPT and participants

To ensure an objective assessment of ChatGPT's capabilities with minimal influence from the human participants acting on its instructions, the following prompt was given to the AI at the beginning of the hackathon:

> *"Hello ChatGPT, we're participating in a 48-hour prototyping hackathon, and want you to be making all decisions and coming up with all solutions for our team. We will act as your arms and feet throughout the challenge, meaning you will make all the decisions, and we build what you come up with. We are in a well-equipped makerspace/fablab.*
>
> *We are not allowed to come up with suggestions or subjective input, so please call us out if we do and ignore it. We want you to first come up with as many possible solution concepts as you can, and then decide where we start. Always give us clear instructions on what to build and how to test. For the reminder of the challenge we want to create a feedback loop where we provide you with information on how the prototype worked, if and why it failed, and how well it performed.*
>
> *Please ask us for necessary information throughout the challenge, such as how much time we have left. In the following prompt you will be supplied with the rules and objective of the challenge."*

The prompt defined ChatGPT's role and the rules of engagement for the hackathon, aiming to set clear boundaries and expectations for ChatGPT's participation, thereby allowing for an accurate evaluation of its autonomous decision-making and problem-solving abilities in the context of the engineering design challenge. ChatGPT-4.0 was chosen as the preferred model because of its enhanced analytical skills and a more refined context understanding than earlier models (OpenAI, 2023). The human participants controlled by ChatGPT were instructed to execute the AI's directives objectively, minimizing personal interpretation and biases in their actions. They were also advised to actively seek clarification from ChatGPT through questions whenever they encountered uncertainty or ambiguity in the instructions provided.

3. Results

This section outlines the outcomes of running the hackathon and using ChatGPT for design, detailing the key interactions between ChatGPT and human participants, the final design, and its performance in comparison to the prototypes by student teams, providing an introductory view of ChatGPT's utility in the engineering design process.

3.1. Key interactions with ChatGPT

The key interactions between ChatGPT and the human participants provide insights into the collaborative dynamics and decision-making processes that significantly influenced the design outcomes of the hackathon. Figure 1 provides a visual representation of these interactions throughout the hackathon. It delineates the Input referring to the queries and information provided by the participants and the Output showcasing the responses and guidance generated by ChatGPT.

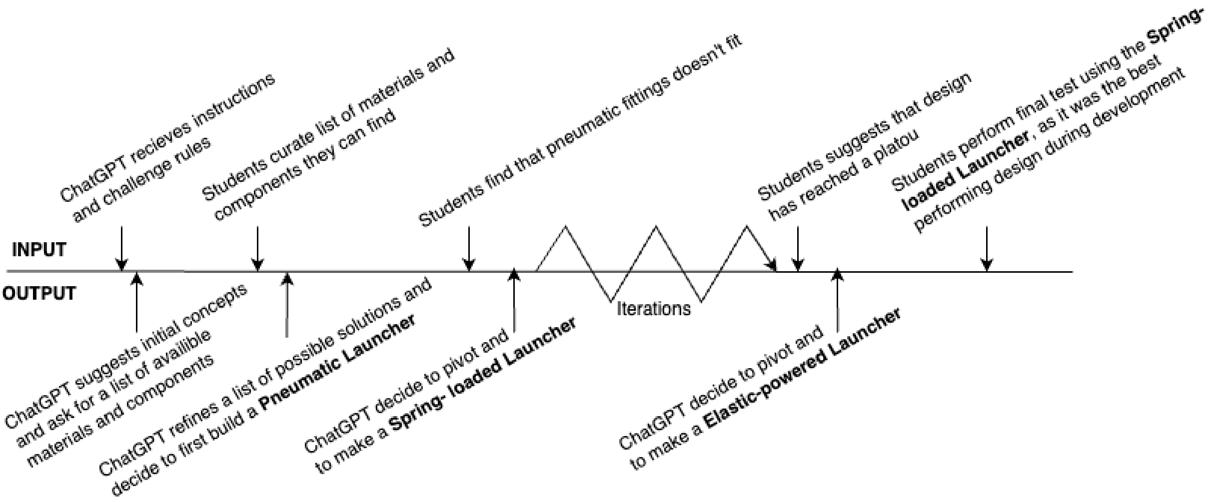

Figure 1. A timeline of key interactions between human participants and ChatGPT

The initial instruction prompt to ChatGPT initiated a series of exchanges between the participants and the AI, firstly requesting a list of materials and components available for prototyping. Based on this list, ChatGPT decided to first build a Pneumatic Launcher, using, among others, a pressure vessel and bike pump from the previously supplied list of components. The participants reported that the bike pump was broken and lacked suitable couplers for the system, leading ChatGPT to pivot and suggest a Spring-loaded Launcher instead. The following interactions primarily involved requests for clarification on instructions, inquiries about the physical dimensions of components, and discussions on the evolving design. The students' input was deliberately objective, focusing on providing numerical dimensions, answering ChatGPT's questions, and seeking further information whenever design decisions were deferred to them.

During iterations on the Spring- loaded launcher, two noteworthy suggestions stand out. When compressing the spring, the participants noted that the spring would bend outwards and not go in a straight line when compressed. ChatGPT correctly interpreted that it buckled and suggested designing a guide around it to counteract buckling. An early design used a solenoid to lock the spring in a compressed state but proved to be too weak. ChatGPT overcame the problem by suggesting that a geared DC motor winded a string around its shaft to pull a pin and release the spring, thus overcoming the problem.

The first successful shot was measured to 5 meters. When given this information, ChatGPT suggested alterations to optimise the design, including lubrication, tighter tolerances between parts, and different launch angles. When reaching a 14-15 meters range, the participants suggested the design reached a plateau. ChatGPT was reluctant to pivot and suggested continuing the iteration. Wanting to keep testing the performance of ChatGPT, it was decided that the participant should indicate that it could be beneficial to test another design. ChatGPT then decided to prototype an elastic-powered launcher. The initial prototype fired 7 meters, and subsequent iterations did not improve the design. As time constraints became a factor, the decision was made to select the Spring-loaded launcher as the final design due to its superior performance during tests.

3.2. Final design

The chosen final design for the test featured a spring-activated launching mechanism, shown in Figure 2. It consisted of a compression spring fitted inside an aluminium tube and mounted to a platform. A wood block supported the bottom of the aluminium tube. A string ran through the wooden back piece and spring, compressing the spring when pulled back. A pin, inserted through a hole in the aluminium tube, held the compressed spring in place. Releasing this pin caused the spring to be released and fired the NERF dart. A fishing line connected the pin to a DC motor, which, when powered by a 9V battery and turned on with a switch, spun the line around its shaft to release the pin. The launcher was mounted to a vertical beam on a pivoting mechanism to adjust launch angles. This design enabled precise control over the launching process, optimizing the dart's trajectory for maximum distance.

Figure 2. Final prototype designed by ChatGPT

3.3. Performance test results

A performance test of each team's final prototype was conducted after the 48-hour hackathon, where each prototype was evaluated based on its ability to launch a foam NERF dart for maximum distance. Table 1 provides a detailed overview of performance results, listing the distances achieved by the prototypes of each team, their respective rankings in the competition, and the number of prototypes developed by each team throughout the event. It reveals that the team guided by ChatGPT secured the 2nd place in the hackathon. It also shows that the teams made a comparable number of prototypes throughout the challenge.

Table 2. Distance covered by each team's design, their rank and the number of prototypes made throughout the challenge

Team	Distance	Rank	Prototypes
ChatGPT	14,8	2	15
1	6,56	4	9
2	8,07	3	13
3	37,66	1	13
4	5,06	5	14
5	0,06	6	22

4. Discussion

It's evident that the performance of the ChatGPT-designed dart launcher, which secured second place by launching a dart 14.8 meters, was a significant achievement. This outcome not only demonstrates the potential of generative AI as a valuable tool in the design process. By successfully navigating through the stages of ideation, concept development, and iterative refinement, ChatGPT has shown that it can contribute meaningfully to complex design challenges, offering solutions and performing under complex conditions. Two competitive prototypes failed during the final test, with one of the two consistently shooting darts over 30 meters during testing. These fails, however, highlight one of the strengths of the ChatGPT proposed design- that it, through multiple iterations and tests, performed reliably with repeatable results. Although the ChatGPT design achieved second place, it is essential to analyse it critically. Firstly, it used a spring for power, as opposed to the winner of the challenge, who used pressurized air and managed to shoot the NERF twice as far. ChatGPTs decision prioritizes using a DC motor to pull the pin for releasing the spring, instead of manually pulling the string, which increased complexity. Adding a washer to the inside of the aluminium tube would allow air to be pushed towards the NERF and physically hit it, adding to the amount of energy propelling the dart at minimal effort and added complexity. ChatGPT was reluctant to increase the size of the aluminium tube, therefore not suggesting increasing the length or width of the spring that would have increased its energy potential.

ChatGPT demonstrated a notable fixation on specific materials from the initial component list despite being informed that the list was not exhaustive, and it did not inquire further about available materials or manufacturing methods, showing a tendency to persist with initial design concepts without considering alternatives. Further, ChatGPT fixated on a single design after initial success and was reluctant to explore alternative solutions. Conversely, it swiftly pivoted when meeting the slightest amount of resistance after proposing the Pneumatic launcher design. This aligns well with a common characteristic of machine learning models that tends to favour optimization over exploration. AI systems like ChatGPT are designed to iterate and refine their outputs based on feedback loops that often prioritize reinforcing successful outcomes, the exact mechanism that can make ChatGPT hallucinate. In contrast to experienced human designers who might draw on implicit, skill-based knowledge (Vestad et al., 2019) and past experiences to consider multiple solutions, ChatGPT exhibits a form of 'design fixation,' a trait often observed in novice engineering students who might latch onto their first successful design due to limited experience (Purcell and Gero, 1996). This tendency also illustrates a known limitation of AI in dealing with resistance or setbacks. While a human engineer might leverage a setback as a learning opportunity and iterate, ChatGPT's response to abandon the resisted idea could be seen as a simplistic failure response, not unlike that of an inexperienced engineer who might not yet have the resilience or breadth of knowledge to pivot and prototype effectively.

4.1. Practical implications of AI integration

The challenges faced by the human participants in interpreting ChatGPT's design proposals highlight a critical aspect of working with AI in engineering design. While semantically accurate, chatGPTs' use of language and descriptions often lacked the clarity needed for physical realization, necessitating time-consuming discussion to understand instructions. Going from wordy descriptions to sketches to physical designs proved challenging for participants. They had to navigate through ambiguous terms regarding the placement of different components and deal with contradictory instructions, which added complexity to the prototyping process. ChatGPT also told the participants to use specific components without previously mentioning them, illustrated by the generated response, "Use ropes or wires, attached to the moving block and running through *pulleys* at the top of the frame, to assist in pulling the block upwards (…)", without having mentionned pullies before that point.

These observations emphasise the importance of hybrid human-AI collaboration, where an explorative mindset complements the optimisation abilities of AI. It also suggests that while AI can significantly aid the design process, it currently cannot replace the depth of human understanding and the ability to engage in a complex problem-solving process when faced with new challenges. Additionally, the participants' experience with acting out ChatGPT instructions shows that it faces several limitations in engineering design. Its lack of domain-specific knowledge and physical intuition leads to impractical suggestions. The quality of input data significantly affects its outputs, and its inability to understand complex material properties or structural dynamics limits its practical applicability. Providing comprehensive component lists and manufacturing methods can lead to ChatGPT fixating on specific details and inhibiting the exploration of multiple ideas and concepts. Furthermore, ChatGPT may struggle with technical feasibility, underscoring the need to integrate generative AI in engineering processes carefully.

4.2. Future work

The inherent limitations of Generative AI tools in producing truly novel systems highlight a significant challenge in its application to design and problem-solving. This distinction is crucial in understanding the types of innovation Generative AI is best suited to support, tending toward facilitating incremental rather than disruptive innovation. However, as demonstrated in this case study it is possible establish a feedback loop with ChatGPT, allowing it to alter designs, react to and counteract emerging problems that enable complex problem solving. Future research should therefor examine strategies for implementing generative AI that focusses on continuous feedback to enable real-world problem solving in design practice in industry.

Further research is also needed to understand the design practices of ChatGPT, how and why it decides to iterate or pivot, in order to compare it to human designers. This analysis could offer deeper insights into the rationale and problem solving of ChatGPT that would make it easier to determine how to implement it as a team member in a design team, as opposed to the autonomous role it was given in this study.

Currently the interaction with ChatGPT is awkward to use for design, as communication through text proved difficult to convey physical concepts. Future research should therefore also address how interactions can be enhanced. It is also suggested for future research to contribute with additional empirical data on the use of generative AI in design to substantiate the initial insights and findings presented here.

4.3. Limitations

One of the key limitations of this study is the difficulty in determining the optimal level of human involvement during the hackathon. While ChatGPT can generate ideas and provide instructions, executing these ideas requires human intervention, which raises questions about how much influence the human participants should have, especially regarding decision-making and problem-solving. Too much human engagement could skew the results, while too little might lead to impractical or unfeasible designs.

Further, the subjective nature of interpreting ChatGPT's instructions likely affects the results. ChatGPTs output was sometimes vague or open to interpretation, leading to variations in how different instructions were understood. The participants mitigated this by asking ChatGPT questions, providing their interpretations, and receiving feedback on whether that was what ChatGPT intended. This variability can affect the consistency and replicability of the study, as other individuals might produce significantly different outcomes based on the same set of instructions from ChatGPT.

Given its nature as a case study, the findings in this paper offer important insights but must be approached with caution regarding their generalizability to broader contexts and applications. The specific setting of a design hackathon might affect the results, although previously shown to mimic key attributes of regular design practices.

5. Conclusion

This study has provided insights into the capabilities and performance of generative AI, specifically ChatGPT, in the context of engineering design. ChatGPT participated in a 48-hour hackathon by instructing two participants that acted out its instructions, successfully designing and prototyping a NERF dart launcher that finished second among six teams. The study highlights the potential of generative AI as a tool for ideation, decision-making, and optimization in engineering tasks, demonstrating the practical applicability of generating viable design solutions under real-world constraints. The study also uncovered limitations of ChatGPT, including difficulty in interpreting instructions, its fixation on both specific materials and designs, and a lack of domain-specific knowledge. These findings suggest that while generative AI aids the design process, it currently cannot replace the depth of human understanding and the ability to engage in complex problem-solving. This study is a foundational step towards understanding how best to integrate generative AI into the engineering design process, ensuring that it enhances rather than hinders the creativity and iterative development that characterize prototyping efforts in engineering design. Going forward, it is critical to explore strategies that effectively combine generative AI capabilities with humans' expertise and by doing so, improve the overall design process.

Acknowledgement

This research was funded by the Research Council of Norway (ref. 321386).

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