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Artificial Intelligence & Engineering Design: How AI Impacts a Suite of Design Innovation Methods

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Abstract

Human-centered design process and design methods (DM) are continually evolving. New technologies such as advances in multi-physics simulation capability and enhancements to additive manufacturing capabilities have created significant alterations in the design process. Artificial Intelligence (AI) has the potential to create similar new aspects in the engineering design process. AI has proven to sometimes be a tremendous asset, sometimes be a detriment and occasionally be misused. This research begins with an extensive introduction to AI and its incorporation into design process. The work then takes DM from a design process called Design Innovation (DI) and reports on efforts to incorporate a variety of different AI-based tools to enhance the DM incorporated into that design process. DM such as Journey Mapping, Functional Decomposition, Mind Mapping, CAD and Design Change Data Management, among others, are addressed. The effectiveness of different AI-based tools on the DM is reported. Some AI-based tools have little, or possibly even negative, impact when applied to certain DM while others can significantly enhance the effectiveness of the design process method.

1. Introduction

This paper reports on efforts to use AI-based tools (AI-T) to enhance various design methods (DM) used as part of a specific design process. The AI-T investigated include Chat-GPT Copilot, Miro Assist, Perplexity, CADscribe, Stable Diffusion, Viscom and JAVA as it is used to create a Multiagent System. The design process used is called Design Innovation (DI) [22]. DI is a user-centered design process that leads designers through four major design steps as is illustrated in Figure 1. Each step in the DI process incorporates a variety of different DM. The DM are orchestrated tasks that the design team accomplishes to complete that step in the DI process. The DI process has four steps; referred to as the "4Ds". The first D, Discover, entails engagement with the stakeholders. The focus is on empathy in order to understand not only explicit but implicit needs of the different stakeholders. The second D, Define, uses systems engineering techniques such as functional decomposition and journey mapping to interpret the information gathered in the Discover phase and develop deeper insight into the design challenge. Often this phase ends with the development of the core opportunity statement that drives the design work. The third D, Develop, implements numerous ideation DM including mind mapping, C-Sketch rotational drawing and Design by Analogy to generate ideas to address the opportunity statement. The fourth D, Deliver, provides DM for prototyping and testing strategies as well as creation of other project deliverables such as design pitches and design documentation.

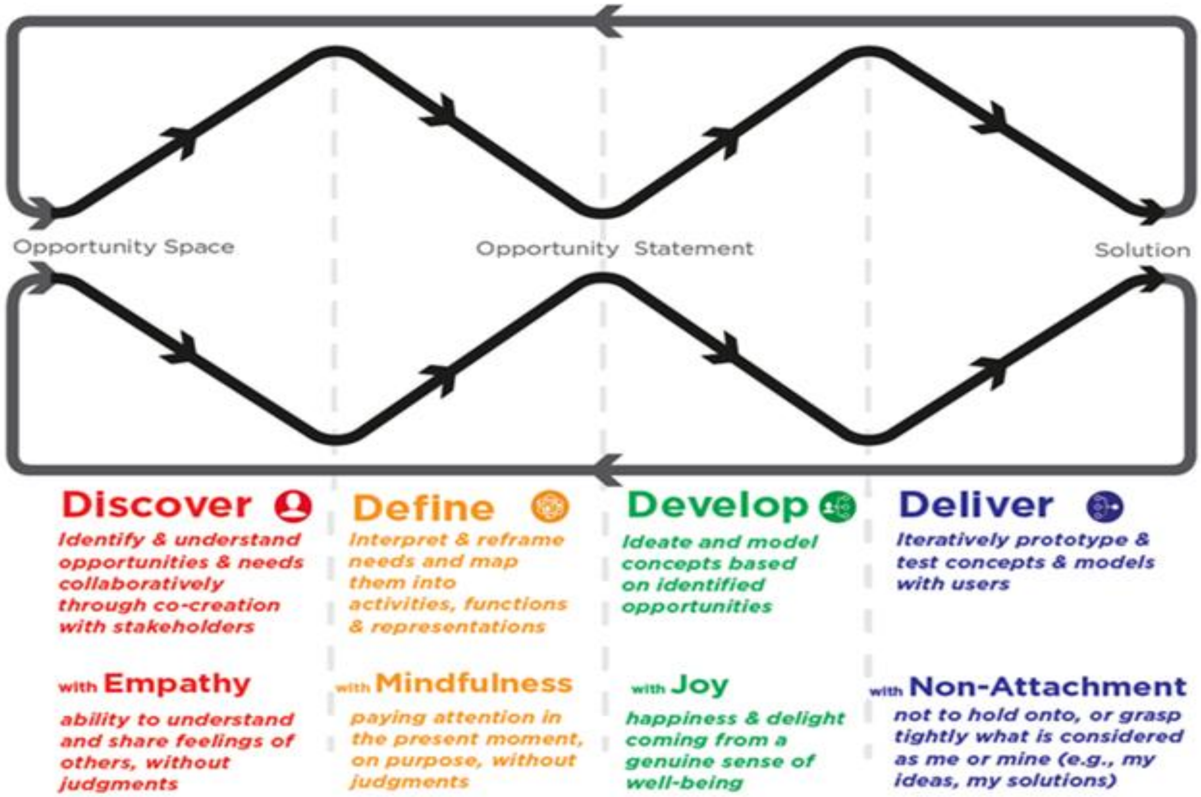

FIGURE 1: 4D DESIGN PROCESS [22]

2. AI Overview and Literature Review

2.1 Background on AI

The rise of Artificial Intelligence (AI) and its effects on a multitude of industries cannot be understated. The concept of AI originated in the 1950's with Alan Turing and the "Turing Test", officially coined as "Artificial Intelligence" by John McCarthy in 1956 (19). AI is a general term for technology that "enables computers and machines to stimulate human learning, comprehension, problem solving, decision making, creativity and autonomy" (19). Under the umbrella of AI are multiple AI-based tools (AI-T) that can assist in the engineering design process.

The first of these is Machine Learning (ML). According to Radhika Jajkumar, "ML refers to the process of training a set of algorithms on large amounts of data to recognize patterns, which helps make predictions and decisions" (20). There are three categories that ML is divided into: supervised learning, unsupervised learning, and reinforced learning (19). Supervised learning uses data sets that are labeled by humans before being fed to the computer to recognize patterns. Unsupervised learning is unlabeled data where the ML system is left to identify patterns and similarities on its own (19). Chat GPT is an example of an unsupervised ML system also known as a Large Language Model (LLM). Jajkumar explains, "LLMs process billions of words and phrases to learn patterns and relationships between them, enabling the models to generate human-like answers." However, she warns, "they aren't thinking like we do, in the sense that they cannot understand fact, logic, or common sense" (20). The third category is reinforced learning where "the system is trained to maximize a reward based on input data, doing a trial-and-error process until it arrives at the best possible outcome" (20).

Deep Learning (DL) is the next category which is a subset of ML. DL systems are designed to emulate the decision making of the human brain (to some extent) by using multilayered neural networks. These layers include an input and an output with up to hundreds of hidden layers, while ML systems will typically only have one or two (19). Once properly trained, DL models can run exponentially faster than previous simulation systems (15). However, DL systems take much longer to train than ML systems. Once properly trained the increased speed is due to the ability to use unsupervised learning to run simulations on multiple layers throughout the neural network. This speed makes DL systems the best option for image and speech recognition, natural language processing, and real time decision making.

Generative AI (GenAI) is the next category which is a subset of DL. Yuan Sun et al. describes GenAI as "designed to generate novel content, insights, and solutions by identifying, replicating, and recomposing intricate patterns within existing data" (5). The key difference between GenAI and the rest of AI-T is that it can create new and complex content in response to the user's inputs (19). There are three primary DL model types that have contributed to the evolution of GenAI.

Variational autoencoders (VAEs) which, “enabled models that could generate multiple variations of content in response to a prompt or instruction.” Diffusion models which, “add “noise” to images until they are unrecognizable, and then remove the noise to generate original images in response to prompts.” And finally, Transformers, “which are trained on sequenced data to generate extended sequences of content” (19). The use of all these AI-T can increase the speed, efficiency, and creativity of the engineering design process. One issue that can arise specifically in GenAI systems is referred to as Hallucinations. Awati states, “An AI hallucination is when a large language model powering and artificial intelligence system generates false information or misleading results, often leading to incorrect human decision-making. Hallucinations are most associated with LLMs, resulting in incorrect textual output. However, they can also appear in AI-generated video, images, and audio” (21). Figure 2 below demonstrates the layers of AI systems and how they fit together along with the dates when they came to prevalence.

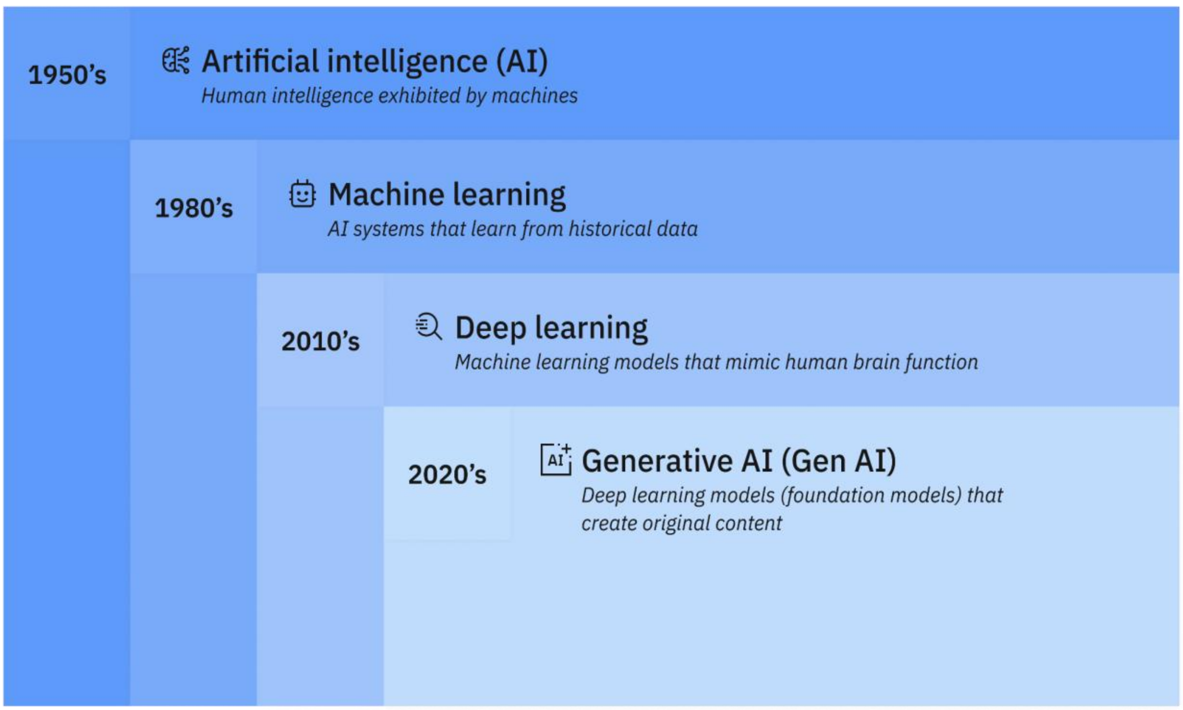

FIGURE 2: LAYERS & TIMELINES FOR AI-T

2.2 Previous Work using AI-based Tools (AI-T) to Enhance Design Process Methods

There is a variety of literature that explains how these AI-T can lead to an improvement in the engineering design process. While, in many cases, the AI-T have not been thoroughly tested for use in enhancing DM, there are some cases where researchers have documented AI-T enhancing efficiency and creativity.

ML systems can use multiple steps to solve multiple problems at the same time whereas many other AI systems are limited in their approach (3). This can be used in the design process as we use historical design data and performance metrics to predict the potential success of new design ideas. Additionally, ML resources aim to improve efficiency in decision making and greatly reduce the time and money spent during the traditional design evaluation methods (6). The sentiment from much of the literature is that while ML systems can be beneficial to the engineering design process, the integration of other AI-T with ML systems is needed for optimal creativity, efficiency, and results. ML consists of the algorithmic makeup of DL and GenAI which will be discussed next (13).

As discussed previously, DL is a specialized subset of ML that uses neural networks inspired by the functionality of the human brain (2, 13, 14, 15, 18). Kalimuthu et al explore a reinforced DL system where a cleaning robot transforms their shape to maximize the floor space coverage (2). Their study revealed that this reinforced DL system, "showcases a consistent learning process, with a continuous increase in the mean rewards." Additionally, "agents trained on one map could efficiently adapt and converge more quickly on an unseen map" (2). Similarly, Ong et al utilize DL systems for fall recognition and forecasting for reconfigurable stair-accessing service robots. They found that the ideal is a Bidirectional Long Short-Term Memory model (BiLSTM) stating, "with its bidirectional processing capturing both short-term and long-term dependencies, demonstrates superior capabilities in accurate fall classification. Additionally, the forecasting results using the BiLSTM model highlight its potential for predicting subsequent values in a time series" (14). Brossard et al describes what is referred to as Deep Learning Surrogates (DLS) which can greatly increase the efficiency of the digital design optimization process. Like other AI systems, the DLS system runs simulations based on the constraints and performance characteristics that the engineering team defines. However, "as those initial simulations are run, they are used to train a neural network, which is set up to take the same inputs and attempts to replicate the outputs of the simulation system. When training is complete, this deep learning model will work just like conventional systems, but much, much faster" (15). These high speeds make complexity less of an issue and allows an engineering team to simultaneously run optimizations across domains. Using the example of industrial wind turbine configuration, they describe how this process can improve the design process and drastically lower the cost and person hours previously required in real world industries (15). Mahboob et al explain two DL networks that can improve the engineering process: Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). They describe CNN as, "a deep learning technique designed specifically for image and video analysis. It uses convolutional layers to automatically extract meaningful patterns and features from images, enabling accurate tasks like object detection, image recognition, and image segmentation. GAN is explained as, "a deep learning technique that consists of two neural networks, a generator, and a discriminator, which are trained adversarial. The generator generates synthetic data, while the discriminator tries to differentiate between real and synthetic data. This process leads to the creation of realistic synthetic data, benefiting applications like image synthesis and data augmentation" (18).

Generative AI (GenAI) can use DL learning models to produce novel ideas (5, 8, 10, 11, 12, 13, 17, 18). Bahn and Strobel state, "Leveraging deep learning generative models, generative AI is capable of producing novel and realistic content across a broad spectrum (e.g., texts, images, or programming code) for various domains based on basic user prompts" (13). There are a variety of AI-T that have GenAI capabilities. LLMs such as ChatGPT, OpenAI, and Google Bard can be used to create unique natural language texts for research paper summaries or outlines for example (8). Meneske explains, "Midjourney and DeepBrain AI are diffusion models that can create diagrams (e.g., concept maps), images, and videos from textual or visual inputs. Engineering education, in particular, can benefit from integrating and utilizing generative AI technologies to improve instructional resources, develop new technology-enhanced learning environments, reduce instructors' workloads, and provide students with opportunities to design and develop their learning experiences" (8). Mattson explores an AI-Tcalled Vizcom which creates a novel rendering of an image based on a user's input of a sketch. Some capabilities cited by Mathtson are: allow freedom to the AI to generate its own ideas, prompt engineering is very important, limit excess distractions in the sketch, and do not include text because the AI cannot deal with it yet (17). Kalota lists some other image generation tools that could add value to the creative process such as, "Bing Image Creator, Craiyon, DALL-E2, DreamStudio by Stability AI, Dream by WOMBO, Midjourney, and Myheritage's AI Time Machine" (12). Muller and Weisz describe the benefits of "Reframing" which is a technique where a GenAI system suggests alternative perspectives or analogies to inspire new ideas and solutions based on the framing and reframing of human inputs. This conversational interface allows for a fluid exchange of ideas between designer and AI which creates interactive dialogue that helps to create novel concepts that may not be possible though traditional DM (10).

There are numerous drawbacks associated with GenAI that are noted throughout the literature. It can be non-deterministic, uncontrollable, or overly generic which means that many trials need to be taken to reach a desired outcome (5). It is also a challenge to incorporate into the curriculum as educators need to be trained and educational frameworks need to be updated (8, 11, 12). Additionally, there are ethical concerns with ways that GenAI can be misused. Deep fakes, loss of jobs, and cheating in education settings are all negative aspects that arise with GenAI (13).

Design by Analogy (DbA) is a specific engineering DM that is part of the 3rd "D" (Develop) in the DI process. DbA can, in some circumstances, be improved with the involvement of AI. Jian et al describe DbA as, "a design methodology wherein new solutions, opportunities or designs are generated in a target domain based on inspiration drawn from a source domain; it can benefit designers in mitigating design fixation and improving design ideation outcomes" (7). There are new opportunities and methodologies for DbA with the growth of design databases, AI technology, and rapidly advancing data science (7). Song and Fu show the effects of an exploration-based approach when it comes to DbA. They find that designers can enhance creative process, quality, and originality of design processes by exploring a wider range of analogical sources (9). This also relates to the idea of "Reframing" which was addressed above in the GenAI review. By constantly framing and reframing DbA prompts, the AI systems can work in collaboration with designers to produce novel ideas and improve the design process (10).

3. Research Questions and Process

The DI design process described above (see figure 1) contains dozens of different DMembedded in each of the four stages (Ds) in the process [22]. Most implementations of DI choose a subset of the DM to incorporate into that specific design project. The work below selects a set of DM that were used in a specific design project that was part of an engineering design course at Westmont College in the spring of 2024. We also add a few additional DI methods and use a different design prompt to evaluate those methods. This is done as these additional methods are so prevalent in common DI implementation.

In this context, the specific research question driving the work in this paper is given below.

Research Question: Can a select set of AT-T enhance a specific set of DM used as part of the DI process?

The exemplar design project used to frame the investigation of the research question was part of a junior level design engineering course. The design project's focus was to create an educational STEM kit for Ecuadorian children aged 6-17 teaching them mathematical and other STEM principles. One of the products created, which later was delivered by the engineering students to the children in Ecuador, included a ping pong ball being shot by Player 1 with an aimable catapult into a soccer-like goal. There was a goalkeeper being controlled by Player 2 behind the net with an Arduino controller. The Ecuadorian children learned to assemble the kit by following directions and doing basic wiring and assembling. They learned basic concepts of forces such as acceleration and spring force and enjoyed a competitive and engaging game. As the students followed the DI process, numerous DM were used to create the STEM kit. AI-T are investigated for potential to enhance many of these DM as described below. Note that for a few of the DI methods, a different application was used to test the impact of the AI-T. This was done in a few cases as the research team did not have the data from the "exemplar" project to sufficiently test the AI-T.

4. Results

The Table 1 below documents the different DI step in the 4D DI process along with the method, the AI-T and the summary of the resulting effectiveness of the implementation. The sections below the table provide details of the research efforts and outcomes.

TABLE 1 – OVERVIEW OF THE RESEARCH RESULTS

DI Step	DI Method	AI-T	Summary & Recommendations
D1 - Discover	Personas / Scenarios	ChatGPT	Helpful in certain contexts – LLM must be trained correctly to get helpful responses
D2 – Define	Functional Decomposition	ChatGPT	Helpful if prompts are engineered correctly – best used in coordination with human generated function lists
D2 – Define	Affinity Grouping	Miro Assist	Not recommended – simply didn't create good lists of stakeholder feedback
D2 – Define	Journey Mapping	ChatGPT, Copilot, Perplexity	Sometimes helpful if prompts are engineered correctly – must be used in coordination with personas and scenarios
D3 - Develop	Pugh Charts	ChatGPT, Copilot, Perplexity	Sometimes helpful if prompts are engineered correctly
D3 - Develop	Mind Mapping	Miro assist	Very helpful – quick and useful maps were generated
D3 - Develop	Design by Analogy	ChatGPT, Miro assist	Very helpful (Miro only)
D3 - Develop	Rotational Drawing & Image Generation	Viscom	Not recommended – translation of text into schematics did not create embodiments that met customer needs or functional requirements
D4 - Deliver	CAD	CADscribe & Stable Diffusion	Limited usefulness – only very simple CAD was accurately generated
D4 - Deliver	Prototype and Design Revisions	ChatGPT, Java	Very helpful – but must be coded

4.1 D1 (Discover) Methods

4.1.1 Relating Stakeholder Interaction with Personas/Scenarios Creation and LLM

Personas are a depiction of what a typical or extreme user is like. It aggregates and maps behavior patterns of actual users, based on stakeholder engagement such as interviews, into archetypal profiles, allowing focused study based on these classifications. We investigate whether a large language AI model will be able to summarize and present data that can be used to form these personas.

By accessing online user feedback from analogous STEM educational products, we trained the LLM to respond in ways that aligned with the past users' concerns and needs from the product. Since we are testing on the Junior design project with STEM kits, we scraped reviews from the KiwiCo website, a company that designs and distributes STEM kits to children. We were able to give ChatGPT large amounts of user data in the form of a CSV file. Once we had a trained LLM persona, we tested it against a non-trained LLM to see how knowledge of the reviews affected the results. To test the results, we asked both the trained and untrained LLM "what are some attributes this STEM kit should include so that you are most satisfied with the product?" The answers from the trained LLM, while accurate to the summarized information of the user feedback used to train it, were not substantially different from the untrained LLM. However, that does not mean that the use of the AI-T is not helpful if used in a different manner.

We next tested the trained LLM's effectiveness in creating personas based on interview notes. We gave the LLM notes from an interview with one of the most important stakeholders and told it to summarize the notes into a persona. Then we asked questions that might come up during the design process and took note of how accurate the responses were. We began by asking the same question as the general user persona "what are some attributes this STEM kit should include so that you are most satisfied with the product?" It gave responses different from the untrained LLM that were more in line with the primary stakeholder's response. We also asked questions that were easy to answer based on the actual interview notes. For example, we asked: "how many kids do you expect to attend?" and the responses stayed true to the primary stakeholder's response.

Our conclusion is that using the AI-T to help with organizing stakeholder data is very helpful because this part of the design process was tedious and honestly, not very fun. The results from the LLM responses stayed true to the sources it was given and it was able to create a persona that the design team could interact with.

4.2 D2 (Define) Methods

4.2.1 Functional Decompositions using LLM's

Functional decomposition breaks the operation of a complex product into individual tasks so that the tasks (functions) are easier to address. The tasks are what the product needs to do, not how it will do those tasks. LLMs can help with basic identification of these functions, however, the functional description should be manually revised after receiving outputs.

When evaluating how an AI-T might assist in functional decomposition using LLMs, ChatGPT was the model that gave the most accurate responses. When we plugged our Junior Design prompt into ChatGPT and asked for it to give a functional decomposition of individual elements, it output ideas that were very similar to the manual list we had created.

2. Interactive Learning

- **Activities and Experiments:**
  - Simple circuits and electricity experiments.
  - Chemical reactions with safe household items.
  - Engineering challenges using everyday materials.

3. Skill Development

- **Critical Thinking and Problem-Solving:**
  - Puzzles and challenges that require logical thinking.
- **Creativity:**
  - Projects that encourage design and innovation.

Resources and Tools

1. **Instruction Manuals:**
   - Age-specific guides.
   - Illustrated and easy to follow.

FIGURE 3: CHATGPT PARTIAL OUTPUT FOR FUNCTIONAL DECOMPOSITION

Figure 3 shows parts of the ChatGPT output when asked to create a functional decomposition for our Junior Design project. It successfully output functions that could be used for idea generation. The output partially mimicked the manually created output. The output of functional decomposition assists brainstorming new ideas. There is some “prompt engineering” involved in making the output most helpful. If the prompt is extremely specific and uses the word “functional decomposition”, the results are quite helpful. Note that this need for insight into how to provide the correct prompts is applicable to other AT-T and other DI methods. Also, there is a correlation between the training of the LLM and the need for nuances in the prompts to avoid bias in the AI-T output. Many researchers have written on this subject. In conclusion, AI and specifically LLM’s such as ChatGPT can be extremely helpful in the functional decomposition part of a design process.

4.2.2 AI Assisted Affinity Analysis

An affinity grouping DM works to organize stakeholder input into groups that allow for prioritization of the stakeholder input. This organizational technique is critical in order to keep the voice of the customer in the driving position as the design process progresses.
AI assisted Affinity grouping needs work and time to be effective in augmenting the DI the design process. Miro Assist's Affinity Analysis template was used and was unsuccessful at properly formatting the affinity groups from the stakeholder information.

4.2.3 Journey Mapping and AI

Journey Mapping is an important part of the D2 (Define) stage, as it allows the engineering team to visualize their stakeholder's interaction with the product and therefore decide what areas need to be improved based on the stakeholder's thoughts and emotions at each stage. A journey map is a map of the activities that a persona will go through as it interacts with the proposed technology. The activities are arranged in chronological order. Emotions and information transfer can also be added for some activities. AI can assist this stage with its ability to offer solutions, changes, and improvements to the stakeholder's problem based on imputed stakeholder information and their emotions at various stages.

For most of the testing, the sample opportunity statement "How might we design and integrate an Autonomous Vehicle System for the future of Singapore?" was used. This specific example was used because a detailed and curated journey map and personas for this project were available. The ChatGPT AI-T was given the persona of Adam, the 32-year-old financial advisor who does not own a car and has a very active lifestyle that requires frequent travel around the city. ChatGPT was able to effectively generate and map a solution to this problem, showcasing Adam's interactions with the proposed ride-share app that the engineering team could make to call a taxi service to get him where he needed to go. ChatGPT created touchpoints, user actions, and offered quality-of-life improvements at each stage it created. When ChatGPT was asked to make a different solution if Alex didn't have a phone, it created and mapped his interactions with a kiosk system, showing that AI is able to effectively create and map solutions that had certain limitations.

When ChatGPT was told that Adam was unhappy with the wait time for his ride (utilizing the phone app solution), the AI revamped the "waiting" stage, suggesting placing more vehicles in busy areas of the city and offering a built-in productivity software into the app as an improvement opportunity. This shows that AI can improve its previous suggestions based on user feedback. However, after being told to improve upon its previous suggestions many times sequentially, the AI-T eventually began to repeat previous improvements, showing that it does have a limit in this area.

ChatGPT can make an emotional graph using ASCII symbols and emojis, as well as a chart that contains the points of information transfer and improvement suggestions. It is through a combination of these graphs and charts that ChatGPT can build a full journey map. However, other AI-T such as Copilot and Perplexity do not possess the capabilities to make graphs or charts, making them a tool that is only suited for the description of the chronological tasks. ChatGPT's ability to predict a stakeholder's emotions at each task of a Journey Map was also lackluster. Only ChatGPT could produce this information and then only produced "happy" or "sad" designations. Even these designations were often suspect or inaccurate.

However, ChatGPT is very good at predicting potential problems for a given journey map and offering suggestions for improvements based upon them. When given a Journey Map for a High School Shop Program with the goal of teaching students how to work a Mill through a die creation project, ChatGPT offered potential problems and improvements for each stage of the map. For example, ChatGPT said that a problem for Stage 2 was die sizing. It may be that students' nervousness about the precision required to get the die down to size may lead to mistakes. It suggested offering scrap metal to practice on to build up their confidence. However, when Perplexity was given this same prompt, it offered little suggestions for potential problems, showing that web scraper AI systems may not be the best at predicting potential problems.

ChatGPT provided the best results for Journey Map creation; however, Copilot is still good if a team only requires suggestions for improvements. While Copilot can outline a Journey Map, training is required to make the AI understand how a Journey Map is supposed to be formatted and was not able to associate emotions with the stakeholder tasks.

To get the most from an AI-T's ability to assist with a Journey Map, some prompt engineering is helpful. Providing your opportunity statement and your stakeholder's basic information, such as age and lifestyle, is helpful. If the solution to the stakeholder's problem is already known, it is recommended to provide the AI with a basic outline of each stage of stakeholder interaction with the product.

4.3 D3 (Develop) Methods

4.3.1 Pugh Charts

Pugh Charts are an important part of D3 (Develop), as they allow the engineering team a way to rank order, or down-select, potential design solution concepts. This is normally done when only a small number (<10) of concepts are still being considered. Each concept is ranked against a datum concept with the rankings being organized in categories of weighted stakeholder needs (often taken from the affinity groupings).

The creation of the Pugh Chart can take significant time because giving each concept a ranking grade for each stakeholder need against the datum can be difficult and subjective. This is often done in a team meeting. AI-Ts can offer the ability to make the Pugh Chart easier for the engineering team, as it is able to generate the Pugh chart, evaluate the alternative concepts, and create concept rankings.

ChatGPT was provided with the different potential concepts and the stakeholder needs. The AI-T was asked to weigh each stakeholder need and give an explanation for why it weighted it that way. It was then asked to pick a datum concept and rank the other ideas based off comparison with the datum across the weighted stakeholder needs.

This process takes significantly less time than generation of the Pugh Chart by hand in a group setting. The LLM was also able to give justification. That being said, it is difficult to know how much validity the AI-T generated Pugh has. In addition, the group process of creating the Pugh chart, while time consuming, was also helpful in crating group consensus on the path forward for the design.

The decision that the AI-T made regarding the weights of the stakeholder needs seemed reasonable. However, it may be helpful to provide the AI-T with the stakeholder weights and datum as opposed to allowing the AI-T to generate them. The weights for the stakeholder needs must be based on the actual stakeholder input which the AI-T may not know. Also, Pugh analysis works best when the datum in a "middle of the road" concept.

As an example, ChatGPT was given the Junior design problem "Design a reproducible educational kit that teaches 9–14-year-old Ecuadorian children technical skills and teamwork." An example Pugh Chart was provided to the ChatGPT AI-T. Using the example chart, ChatGPT was successfully able to use the selected datum of the remote-control car concept to rank the other concepts against it. When ChatGPT was told to update the stakeholder needs (1st column) weight distribution of the values in the Pugh Chart, it successfully did so and still was able to calculate for the best option based upon these new criteria as seem in Figure 4.

Both Perplexity and Copilot were also tested for their development of Pugh Charts. Neither was able to produce the level of sophistication and reliability that ChatGPT did. Perplexity was not able to justify the decision it made on weights and Copilot had trouble accessing the input information and making the Pugh chart. If the design team requires the AI-T to only evaluate their Pugh Chart and not generate one, it is recommended that the chart be provided in CSV format. However, if the team is utilizing OpenAI's GPT-4o Model, then it is also worth noting that ChatGPT may require the chart in text (txt) format for evaluation if the server is busy.

Criteria	Weight	Remote Control Car (Datum)	Programmable Catapult	Goalie Shootout Game
Reproducibility for a Poorer User	7	0	1	0
Promotion of Teamwork	8	0	-1	1
Fun	9	0	-1	1
Technical Skills Taught	10	0	1	0
Appeal to Wide Age Range	6	0	0	0
Completion Time (30-60 mins)	5	0	-1	-1
Appropriate Challenge for Age 9-14	10	0	0	1

FIGURE 4: CHATGPT OUTPUT PUGH CHART FOR DOWNSELECTION

4.3.2 Mind Mapping

Mind Mapping is an organization DM to archive ideas created in the D3 (Develop) stage of the DI process. A team creates an opportunity statement, which is a one sentence statement describing the goal of the product to fulfil stakeholder needs. The opportunity statement is put in the middle of this mind map or "web" of soon to be created ideas. Ideas for meeting this opportunity are generated, first individually, then as a group. The ideas are placed on the mind map and then a category for the idea is identified. The category provides the possibility for generation of additional ideas. Research shows that this DM for capturing ideas generates significantly more ideas than traditional brainstorming. The ideas are also shown to have increased quality and novelty [22].

Miro, and specifically their AI component, Miro Assist, was used to develop our Mind Maps. We found that Miro Assist in the Mind Map portion of the design process was extremely helpful in idea generation.

We conducted an experiment where we manually created a mind map as a group of four. Then, we used the same prompt with Miro generated outputs. Our prompt was simple: how to stop global warming. We used 20 minutes to generate our mind map and developed some interesting ideas. We used the same prompt in Miro's mind map feature, then expanded the web with Miro Assist generated topics in a matter of seconds. The outputs were all specific and organized by

Miro Assist. Miro succeeded in developing a superior set of ideas in both quality and quantity of ideas.

In conclusion, we highly recommend the use of Miro Assist in the mind mapping design stage. It is easy to use, outputs ideas in a split second, and apparently has a large database. The more specific you can write the prompt, or opportunity statement, the more accurate the outputs from the Miro created mind map will be.

4.3.3 AI Assisted Design by Analogy

Design-by-Analogy (DbA) is a DM where designers draw inspiration from analogies in different domains to create innovative solutions. This approach can lead to more creative and effective design outcomes by leveraging ideas from different realms. It is common to use the biological realm or related products or even grammatical similarities as analogous inspiration. In this case the effectiveness of two A-T, ChatGPT and Miro for DbA were evaluated.

Initially, ChatGPT was utilized to generate a mind map on animals that propel objects. However, the results were limited, consisting primarily of a list of animals with minimal elaboration on their propulsion mechanisms. To achieve a more in-depth exploration, the study was expanded by asking the AI-Ts to include extreme cases within biological realm. The goal was to gain deeper insights into the mechanisms behind animal propulsion, examining why certain animals are capable of propelling objects at greater speeds or distances. Miro, utilizing its Miro Assist feature, not only generated and expanded on specific topics but also provided comprehensive support, including insightful questions, ideas, and the summarization of complex mind maps. Additionally, it offered grammar corrections and enhanced clarity.

In contrast, ChatGPT's responses, especially when addressing extreme cases, were less detailed and mainly focused on listing animal names without further elaboration on their propulsion characteristics. This comparative analysis demonstrated Miro’s superiority in supporting the development of detailed and insightful DbA-inspired mind maps, positioning it as a valuable tool for advancing research within the DbA framework.

4.3.4 Rotational Drawing Activities and Image Generation AI

Rotational drawing, often called C-Sketch or Brain Writing, is an ideation DM that incorporates both individual and group components into the activity. This is often done following a mind mapping activity as the rotational drawing can take the individual ideas on a mind map and help create more full-system concepts. Each individual on a design team is asked to draw three separate concept systems on a single large piece of paper. Again, the mind map may provide some input for the three systems. Often approximately 15 minutes is given for this initial part of the DM. Next your paper is rotated to your colleague who has a set period of time to augment your ideas (approximately 10 minutes). They may add to, clarify, alter or combine parts of your systems. No cross talk is allowed in this time. After a time, the drawings are again rotated to allow for another colleague's input. The activity is complete when all group members have augmented each drawing. Group discussion and further ideation complete the process.

AI can be very good at generating images. The Viscom AI-T was used for this work. The test that was performed included asking Viscom to create ideas given our initial sketches, just the opportunity statement or both. When providing only initial sketches, the drawings Viscom created were not very helpful. When some prompt engineering was used, the Viscom generated drawings were far more helpful. Vizcom AI has an option of how much the generated image is influenced by the sketch vs the prompt. By testing multiple different ideas, it seems like 80-90% drawing influence gave the best balance. However, as we tested lower quality sketches (where AI alterations might be helpful for clarifying ideas), the AI image seemed limited by the quality of the source drawing. In other words, if the drawing was clear, Vizcom could interpret the idea well, but if the drawing was low quality and not too detailed, it had trouble making out images. Given the time it took to give Vizcom the drawing and engineer a good prompt, the value it adds to the activity is likely not sufficient to justify its use.

4.4 D4 (Deliver) Methods

4.4.1 AI Assisted CAD

AI-T assisted CAD generation was explored in different forms. Initially, providing a text description and requesting a 3d model was explored. This often did not create a 3d model with reasonable fidelity. For example, as can be seen in Figure 5, asking the AI-T CADscribe to produce a garden stake with specific features does not produce a usable output.

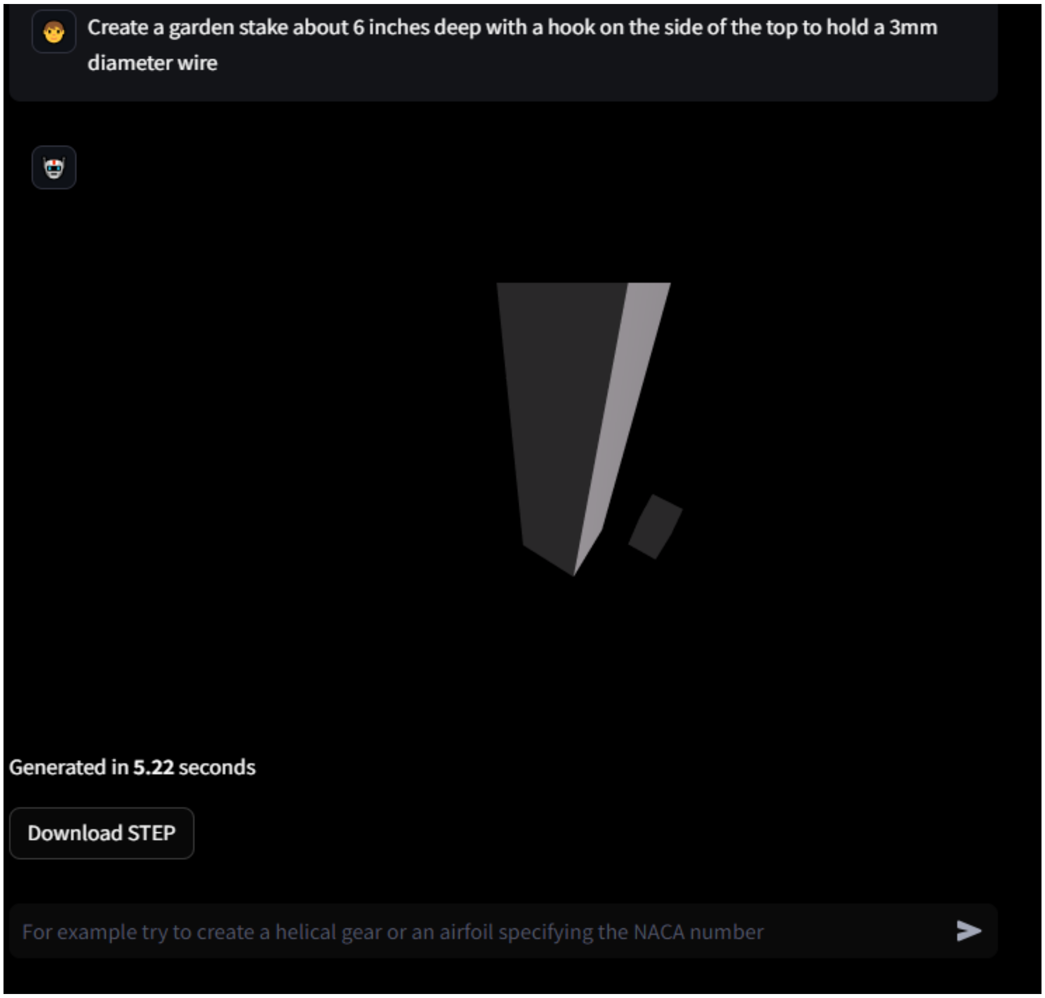

FIGURE 5: CADSCRIBE GENERATED 3D MODEL OF A SIMPLE GARDEN SPIKE

An alternative approach would be to request that the AI-T generate the stl file from text, but this seldom produces a syntactically correct file. The most promising approaches appear to be to have the AI-T modify existing parametric models.

The field of generating a 2d image based on a text prompt appears more promising. The evaluation primarily used Stable Diffusion (version "V1-5-pruned-emaonly.ckpt") and focused on generating an image that could be directly traced by the user into a "sketch" to generate a solid body in CAD software. Note that this is not the intended purpose of the software; its constructed intent was to create artistic renderings of the text prompts. A representational sample is given (Figure 6) with the prompt of: "10 tooth gear, side view, orthographic projection, technical illustration, blueprint style, precise lines."

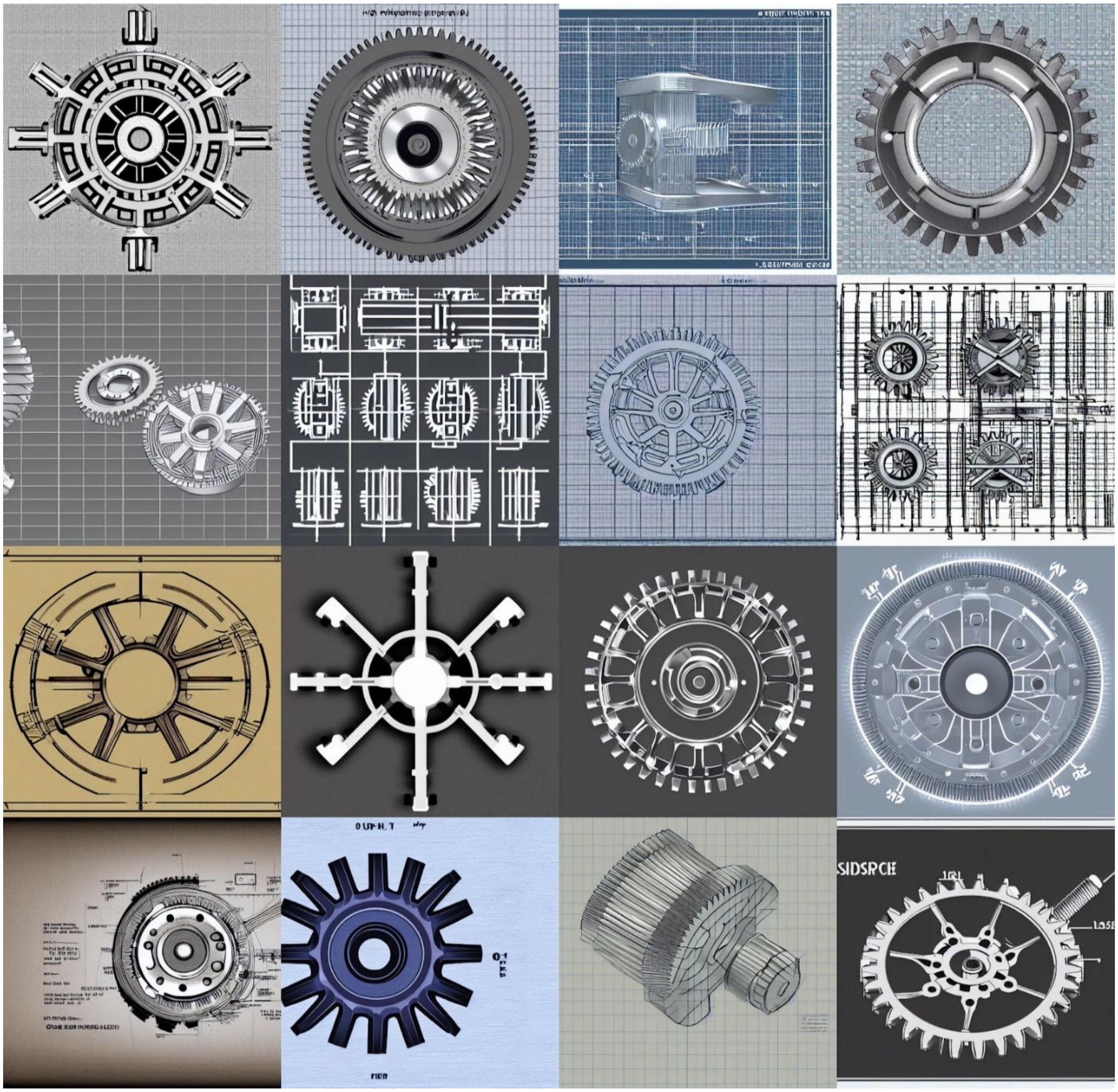

FIGURE 6: AI-T OUTPUT 10 TOOTH GEAR SKETCHES

It is worth noting that of the 16 gear- or sprocket-like things produced, none had 10 teeth, and several disobeyed the “side view” token as well.

However, one particular set of testing produced results that were potentially more useful: the set of prompts describing organic subjects.
An example of a prompt used is: “rose petal, outline, side view, orthogonal projection, technical illustration, blueprint style, precise lines” with the accompanying negative prompt of: “3d, color, irregular”

FIGURE 7: AI-T OUTPUT ROSE PETAL SKETCHES

Again, the images produced are not in a form immediately conducive to tracing into a CAD sketch, but they could provide useful reference or concept art for a contoured biological piece, a subject which remains difficult to produce in CAD.

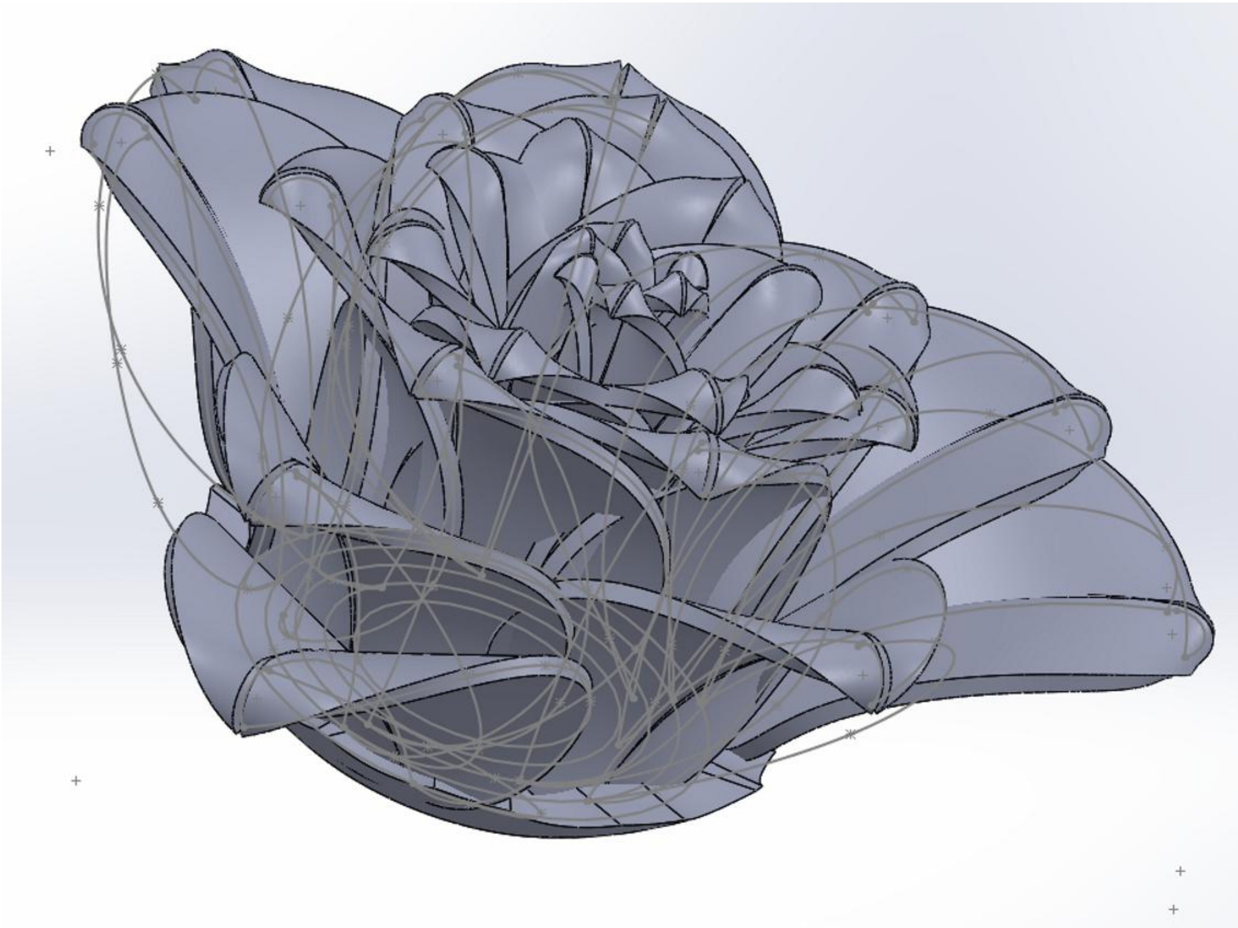

FIGURE 8: ENGINEER'S ATTEMPT AT A "CONTOURED BIOLOGICAL PIECE," SPECIFICALLY A ROSE

4.4.2 AI Assisted Prototype and Design Revisions

Prototyping is a main focus point of the D4 (Deliver) step in the DI process, allowing engineers to build the solutions that were decided upon in D3 and iteratively test them before final implementation. When iteratively testing a prototype, it is inevitable that engineers will have to make revisions on their design, as there will likely be opportunities to more fully meet design requirements. However, developing a schedule with critical path deadlines and determining Key Performance Indicators (KPIs) for those revisions can be a challenging task, leading to the desire to automate the process. While Generative LLMs can provide KPIs and a rough estimate for an implementation date, they are not normally specialized enough to provide reliable decision-making support for the designers.

A Multi-Agent System (MAS) of 4 Machine Learning (ML) agents specifically trained to handle an individual aspect of the revisions process can provide accurate, reliable information due to its checks and balances system and high specialization. Users enter various information about their revision, such as what the change is, how quickly the change needs to be implemented, and how bad the schedule impact is as a result of the change, and the MAS is able to output an optimal implementation date and the determining KPI(s). While the technology to build the MAS easily exists through many different services such as Microsoft Power Agents and Google Cloud AutoML, all of them require a hefty subscription price, and they all pull from Generative LLMs to produce their information. This means that to build a proper Multi-Agent System that pulls its information from reliable databases containing past Engineering Change (EC) information, it must be coded from scratch using an appropriate programming language.

For this specific iteration of the MAS, Java was the chosen programming language. Two external packages were utilized to build the MAS, the Java Agent Development Network (JADE), which allowed for the creation and communication of the four agents, and the Watekero Environment for Knowledge Analysis (WEKA), which allowed for the creation of the various ML algorithms. All four agents, the “Negotiator,” “Optimizer,” “Predictor,” and "Supervisor,” follow a similar structure. The “Negotiator” waits for a revision request to be entered via text. Upon receiving the request, it initializes the “Optimizer” agent, which classifies the revision based on its configuration and user-inputted impact information before producing a date found through nonlinear regression. Once an optimal date is found, the “Optimizer” tells the “Negotiator” the result, which triggers the “Predictor” to find the KPI in regard to the revision’s configuration and the date via a decision tree model. When the KPI is found, the “Predictor” notifies the “Negotiator,” which compares the results against a rule set by means of a rule set classifier to ensure that the determined Optimal Date and KPI are satisfactory. If the results are deemed unsatisfactory, the “Negotiator” prompts the “Optimizer” and “Predictor” for reevaluation until an adequate result is found. From there, the “Negotiator” notifies the “Supervisor” of the results, which performs its own check against a separate rule set before sending the information to the human operator. If the “Supervisor” deems the results to be inadequate, it notifies the “Negotiator” and directly prompts the “Optimizer” or “Predictor” for reevaluation.

Each of the four agents contain their own dataset that are used to train their ML algorithm. However, because companies rarely publish their data on the revisions process, ChatGPT had to be prompted to build the datasets utilized for testing. The datasets were checked and verified by a human to ensure that they only contain explicit, valid data. However, when constructing a MAS for an organization, they may be able to utilize their existing datasets. This approach ensures that the algorithms are developed based on accurate and real-world data, enhancing the effectiveness and reliability of the system.

Upon completion of the MAS, various prompts were provided to it to test the effectiveness of the system. The revision titled “Add Lettering to Remote Control” was a significant change implemented during Junior Design. The MAS was told that this revision had a low urgency, but high schedule impact, and it determined an optimal completion date of April 2nd, 2025, with the KPI being the people involved. It is important to note that the MAS assumes that the human operator is an employee for a company and must go through a process to implement the revision, beginning with obtaining approval, followed by the construction of the change, followed by testing before it is finally incorporated into the end product. As a result, most optimal dates for revision implementations that are outputted by the MAS are at the end of 2024 or later. For the Junior Design prompt “straighten wheel attachment points” the MAS was told that the revision had a high urgency and a major impact on the team’s schedule. The MAS produced April 19th, 2025 as the optimal implementation date and the KPI being the Mean Time to Resolution (MTTR). The MAS is also able to produce an optimal date and KPI for smaller, less urgent revisions. However, it is not without its occasional errors. For the Junior Design prompt “add plastic film to wooden ramp” the MAS was told the revision had a high urgency with a major schedule impact, and outputted an optimal date of June 6th, 2025 and its KPI being the people involved. The optimal date is too conservative (too late), especially considering how the building and implementation stages (including adding the plastic film) should be completed before the “straighten wheel attachment points” revision.

Overall, the creation and implementation of a Multi-Agent System to produce an optimal date and KPI for revisions on designs and prototypes of products was a worthwhile effort, and it could easily be created in under two weeks by a team of software engineers for use by other design teams for their specific project. Although testing has revealed that the MAS may occasionally generate errors, supplying the ML algorithms with an abundance of data will enhance their accuracy. Furthermore, the precision of these algorithms can be significantly improved when this data is derived from real-world scenarios. The MAS could be a great tool to assist in the decision-making process of a company in regard to the revisions of their designs and prototypes, telling them how long different solutions to the problems of their product may be in development as well as what to focus on when building and implementing that revision.

Future research of the Multi-Agent System for prototype and design revisions could unveil the full capabilities of the system, such as whether this system could predict the cost of the revision, multiple KPIs, secondary or even tertiary optimal dates, and integration with a company’s calendar system – especially as it relates to critical path. An advanced form of the MAS could even provide a timeline with instructions on what to do at each stage of the revisions process. The MAS holds vast potential for the future, offering numerous capabilities that could revolutionize AI’s assistance with the decision-making process. A small segment of the UGI for the MAS is shown in Figure 9 below.

```
Hello, enter your EC.
I will try and produce an optimal schedule date and predict your KPI.
Jul 23, 2024 1:30:19 PM jade.core.AgentContainerImpl joinPlatform
INFO: --------------------------------------
Agent container Main-Container@10.252.1.38 is ready.
--------------------------------------------
strengthen wheel attachment points
Please enter the urgency of your EC. {low, medium, high}
high
Please enter the impact on your schedule the EC makes. {none,minor,major}
major
EC scheduled. Optimal Date: 2025-04-19 KPI: MTTR
```

FIGURE 9: THE JAVA RUN PANEL OF THE MAS,

5. Conclusion, Future Work and Acknowledgements

This work provides insight into how different AI-based tools can assist in the engineering design process. A substantial overview of AI is first provided in order to frame the discussion. Then, the Design Innovation (DI) process, which has four steps called the four "Ds" is used as an exemplar design process to investigate the use of various AI-based tools (AI-T). AI-T such as ChatGPT, Copilot, Perplexity, Viscom and others are investigated for their potential to enhance DM employed in the DI process such as Personas, Journey Maps, Functional Decomposition, Design by Analogy, Mind Mapping, CAD production and Design Change Processes. The unique contribution of this paper is the assessment of application of a variety of common AI-T to a common set of DI methods. The results are wide spread, in that some AI-T significantly enhanced in the DM and some were not helpful at all. The results should support others using the DI design process, or similar design processes, as they attempt to use AI to augment their engineering design work. Specifically, this work recommends that designers using a DI (or similar) process consult Table 1 for initial recommendations and then consult the section in the paper that describes details for implementation of AI-T for that DI method. Of course, our insights are limited in particular by the specific design context and problem we used to evaluate the effectiveness of the AI-T. The use of the AI-T in other environments may differ significantly. Additionally, this study is not by any means exhaustive, and thus the conclusions here may not hold up upon further investigation. However, we hope that by presenting these results and observations, we motivate others in the community to explore how AI-T may impact their own design work. Finally, AI technology is advancing at an astonishing pace. As AI-T evolve, there will likely be quick and substantial changes in the potential use of AI-T to augment engineering design. Keeping pace with these rapid changes will be a difficult, and important, task for the design engineering community.

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