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Nature's lessons, AI's power: sustainable process design with generative AI

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Abstract

In the realm of process engineering, the pursuit of sustainability is paramount. Traditional approaches can be time-consuming and often struggle to address modern environmental challenges effectively. This article explores the integration of generative AI, as a powerful tool to generate solution ideas and solve problems in process engineering using a Solution-Driven Approach (SDA). SDA applies nature-inspired principles to tackle intricate engineering challenges. In this study, generative AI is trained to understand and use the SDA patterns to suggest solutions to complex engineering challenges.

Keywords: process design, sustainability, artificial intelligence (AI), GPT, Gemini

1. Introduction and research questions

The pursuit of sustainability in process engineering is a critical endeavour in the modern world. Traditional methods, while effective in their own right, often struggle to address the complex environmental challenges we face today. Natural systems, with their intricate and dynamic components, offer a valuable source of wisdom that can enhance the efficiency and sustainability of process design. Nature has always been a source of inspiration for innovation and has led to several scientific design approaches (Livotov et al., 2020; Bianciardi et al., 2023). Instead of imposing our industrial system on nature, we should allow nature to influence our industrial and innovation system. Lessons from nature have the potential to lead the way to sustainability. Nature-inspired principles have been proven to provide effective solutions to many engineering problems (Mas'udah et al, 2021). Several studies have explored the application of nature-inspired principles to innovation. Coppens et al. (2021) proposed a systematic methodology called Nature-Inspired Chemical Engineering (NICE) that utilizes nature as a guide for innovation without directly imitating natural systems. Unlike biomimicry, NICE uses nature as a guide for innovation but does not imitate nature (Trogadas and Coppens, 2020; Coppens, 2021). NICE has shown promise in addressing chemical engineering problems, but identifying the most appropriate bioresources for specific challenges remains a challenge. Similar to the NICE methodology, the implementation of eco-inventive principles identified in natural systems for process intensification outlined in (Mas'udah et al., 2021) reduces the environmental impact of current technologies. However, finding and adapting nature-inspired principles can be a time-consuming process, and misapplying these principles can lead to unintended consequences.

Recent advances in Natural Language Processing (NLP) have opened up new possibilities for the acquisition of design knowledge (Hu et al, 2023). With the increasing availability of generative artificial intelligence (further in this paper abbreviated as AI) such as Generative Pre-Trained Transformers (GPT) by OpenAI (https://chat.openai.com/) or Gemini (formerly Google Bard) from GoogleDeepMind (https://gemini.google.com/), the potential for using AI to facilitate sustainable process design has become a promising area of research. The integration of generative AI into the process of nature-inspired process design has the potential to overcome the limitations of previous studies. Generative AI utilizes machine learning and a vast array of datasets to provide natural language processing, enabling the generation of informative responses. Previous research has explored the potential of AI in solving complex problems by drawing on principles from nature. For instance, Professor Jin (2021) at Bielefeld University has been investigating how AI can borrow successful mechanisms from nature to enhance problem-solving capabilities. Furthermore, AI's ability to recognize patterns in large amounts of data and generate solutions makes it a powerful tool for eco-innovation (Jin, 2021). Generative AI can rapidly identify patterns and relationships within large datasets, enabling it to extract nature-inspired principles and apply them to specific engineering problems. Zhu et al. (2022, 2023) harnessed the power of Generative Pre-Trained Transformers 3 (GPT-3), a distinct Large Language Model (LLM), to craft a repertoire of 500 biologically inspired design solutions. They demonstrated GPT-3's proficiency in crafting inventive and practical design solutions. They also established a framework for formulating concept generation tasks using LLMs.

Although the utilization of generative AI in previous research has demonstrated some benefits, such as the ability to provide more accurate and comprehensive information, as well as the capacity to integrate generated knowledge into the design process more easily, several challenges such as difficulty in controlling information quality and accuracy, the risk of bias, and hurdles in ensuring the relevance and usefulness of information for the specific design task at hand need to be addressed. Therefore, the study seeks to tackle the following research questions:

1. Can generative AI expedite the process of identifying nature-inspired principles?
2. Can generative AI assist in the application of nature-inspired principles for Process Engineering?
3. What are the differences between outcomes for research questions 1 and 2 by engineers and by generative AI?
4. What strategies can be employed to enhance the efficiency of applying generative AI, specifically exploring different types of prompt engineering and their optimal utilization?

This paper is organized as follows: In Part 2, a detailed overview of the current approach to sustainable process design and the adaptation of AI in the current approach is presented. Part 3 illustrates a case study of how AI generates ideas and solves problems in process engineering, followed by conclusions and outlook for future work in Part 4.

2. Research approach

2.1. Solution-driven design approach

The methodology employed in this study adopts the Solution-Driven Approach (SDA) outlined in Table 1, which builds upon our recent study on learning eco-innovation from nature (Livotov et al., 2020). This SDA was modified from the method introduced by Helms et al. (2009) and utilized to identify eco-inventive principles in natural systems for solving eco-engineering contradictions, as previously demonstrated in our research (Mas'udah et al, 2021; Mas'udah et al., 2022). The iterative algorithm begins by systematically searching for biological ecosystems that operate under constant or temporary environmental stress, such as high or low temperatures, extreme sun radiation or other harmful energy fields, as well as exposure to toxic substances or hazardous organisms within the environment etc.

Given the complexity of ecosystems, the second phase of the solution-driven approach aims to comprehensively clarify and specify all essential natural components. Subsequently, Function Analysis is employed to identify all functions of these components and understand how they respond to unfavourable environments. Similar to engineering systems, natural ecosystems may encounter conflicting goals that require exploration to find solutions. For instance, in the case of a plant leaf, the conflicting requirements of reducing water loss while maximizing surface area for photosynthesis present a challenge. Analysing its structure, colour, and other properties can provide insights into how nature tackles this challenge. Therefore, identifying such conflicts of objectives is often crucial in extracting natural solutions.

Generally, phases 2 to 4 of the SDA are highly resource-intensive as the identification and classification of natural inventive principles in natural ecosystems is a challenging and time-consuming task that requires expert knowledge and experience (Mas'udah et al., 2023). Additionally, the utilization of conventional methods may also be limited by constraints in understanding the abstract and complex concepts of these natural principles. Therefore, for this purpose, the integration of generative AI will facilitate the identification of abstract natural inventive principles and suggest solutions grounded in these nature-inspired principles to complex engineering challenges.

Table 1. Modified solution-driven approach for nature-inspired design (Livotov et al, 2020)

Phase	Description (after Helms, 2009)	Modification for extraction of abstract natural principles for eco-innovation
I	Identification of biological solutions	1.1. Definition and classification of environmental stress factors 1.2. A systematic search for biological ecosystems exposed to environmental stress
2	Analysis and definition of the biological solution	2.1. Component and function analysis for the eco-system, its sub-systems (bio-components) and super-system 2.2. Identification of contradictory functions and eco-requirements. Formulation of eco-contradictions 2.3. Identification of the eco-system components responsible for resolving eco-contradiction between opposing functions or requirements
3	Extraction of biological solution principles	3.1. Extraction of concrete biological eco-solutions in the biocomponents identified in step 2.3 3.2. Formulation of abstract biological eco-solution principles in biological terms
4	Reframing biological solution principles in universally applicable engineering terms	4.1. Transformation of the abstract biological solution principles to eco-engineering using universal technical terms 4.2. Comparison to existing abstract engineering inventive principles 4.3. Identification of new natural inventive principles or sub-principles 4.4. Assignment of all inventive principles and sub-principles to the corresponding eco-contradictions
5	Search for engineering domains and problems for the application of the biological solution principles	5.1. Search for eco-engineering problems or problem clusters in different technical domains (for example, in process engineering with the help of environmental impact categories) 5.2. Search for the eco-contradictions in engineering domains similar to the natural eco-contradictions defined in step 2.2
6	Definition of engineering problem	6.1. Definition of a specific engineering problem incl. possible primary and secondary eco-engineering contradictions
7	Application of the biological principles and development of the bio-inspired engineering solution.	7.1. Development of bio-inspired eco-solution (product or process) 7.2. Anticipation of possible new secondary problems and eco-contradictions 7.3. Optimization of existing eco-solution or application of other biomimetic inventive principles and solutions

2.2. Adaptation of solution-driven approach with generative AI

Figure 1 depicts the bi-directional exchange of information and data between Generative AI and human-performed processes. Generative AI is trained to understand and use the SDA patterns to identify abstract nature-inspired principles from natural ecosystems and to suggest solutions to complex engineering challenges. The initial step involves a meticulous exploration of natural ecosystems thriving under unfavourable conditions and experiencing temporary environmental stress. Environmental stress factors encompass external elements or conditions in the environment, such as extreme temperatures, intense solar radiation, exposure to toxic substances, or other harmful environmental factors that can negatively impact living organisms or ecological systems. These stress factors can be natural or human-induced, affecting the health, survival, or functioning of various organisms, including plants, animals, and humans. The selection of these stress factors is guided by their potential relevance to the engineering problem and their likelihood of yielding innovative solutions. It's essential to highlight that the selection of natural ecosystems for solving specific engineering problems is not restricted to any specific singular phenomena, but encompasses a broad spectrum of natural environments. This approach allows for a comprehensive exploration of nature's adaptive strategies and their potential applicability to engineering solutions.

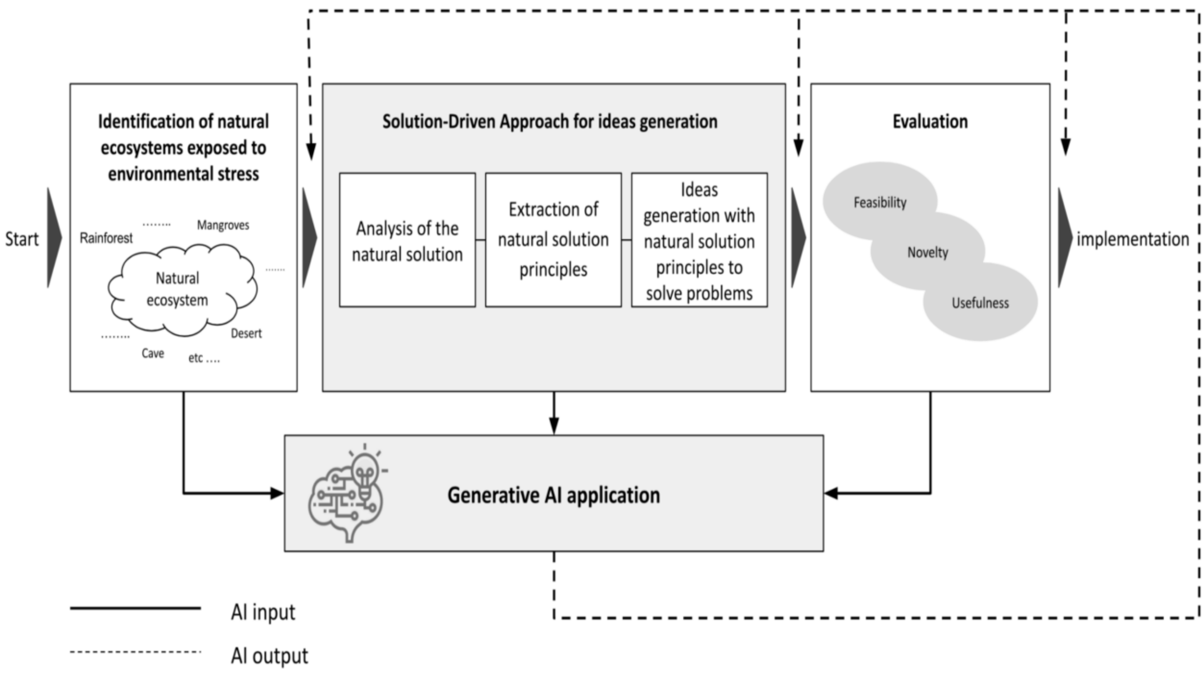

Figure 1. Adaptation of Solution-Driven Approach (SDA) with Generative AI

The next step encompasses the analysis and extraction of underlying natural solution principles, followed by their transformation from abstract concepts into practical applications. By studying the principles governing the survival and thriving of ecosystems in adverse conditions, we can extract valuable principles and apply them creatively to solve a wide range of problems.

The further step focuses on generating ideas based on natural principles to address engineering challenges. As depicted in Figure 2, we use two different types of iterative prompting strategies in order to gain deeper insights into how prompt engineering influences the design solutions generated by the LLM:

a) **Basic prompting** (Brown et al., 2020; Liu et al., 2023): we directly query generative AI with the input and ask it to generate solutions in the form of the desired output.
b) **AI-automated prompting**: together with the basic prompt, we design additional prompts to guide generative AI in generating better results for each task. This technique involves the utilization of automated processes within AI systems to refine and optimize the input queries, enhancing the generation of solutions.

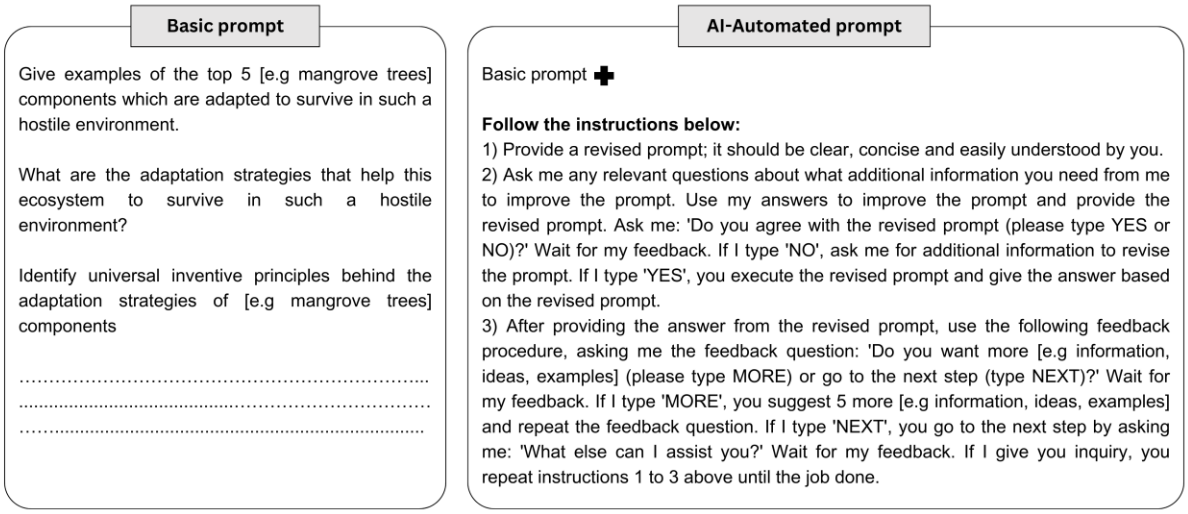

Figure 2. Prompting design for generative AI-based ideas generation

Following this, an evaluation of the generated ideas is conducted to assess their feasibility, effectiveness, and potential for implementation. The metrics used to evaluate the design solutions were derived from the literature (Shah et al., 2000; Shah et al., 2003). In this study, we evaluate the output ideas generated by generative AI through both human evaluation and AI self-evaluation methods. The evaluation of the generated solution ideas as presented in Table 2 involves assessing three criteria with 3 possible measures i.e. their feasibility, novelty, and usefulness with the score range between 0-2.

Table 2. Assessment criteria for generated solution ideas

Characteristic	Rating scale	Description
Feasibility	0-2	0 - Unviable for implementation 1 - Feasible but requires substantial effort 2 - Easily implementable
Novelty	0-2	0 - Common or derivative 1 - Moderately novel 2 - Highly original or unique
Usefulness	0-2	0 - Irrelevant 1 - Moderately relevant 2 - Highly useful

These evaluations criteria provide insights into the viability, originality, and relevance of the generated solutions, aiding in the selection of the most suitable solutions for addressing the engineering challenges at hand. Lastly, these evaluated solutions are applied to solve complex problems in the field of process engineering.

3. Case study and results

This section outlines the leveraging of the Large Language Models to generate solution ideas based on nature-inspired principles for solving problems in a case study. We compared two popular models: Gemini and GPT-3.5, examining their effectiveness in generating creative solutions. Gemini (successor to Google Bard) employs an innovative approach to response generation, presenting users with multiple response drafts. This functionality empowers users to assess and choose the most fitting response for their needs. While it is not a conventional search engine, Gemini enables users to pose general inquiries, foster ideas, and compose written content (Ray et. al, 2024). Furthermore, Gemini's ability to generate creative solutions and its access to a vast knowledge base makes it a valuable tool for enhancing the efficiency and sustainability of process design. Similar to Gemini, GPT-3.5 also known as ChatGPT in its first version, is an artificial intelligence-powered text generator developed by OpenAI (Brown et al., 2020). It is constructed based on the InstructGPT model, a component of the GPT-3.5 series of models (Ouyang et al., 2022). These models were created by transforming a vast instruction-tuning corpus utilized in InstructGPT into a conversational format. It leverages its extensive training data to generate coherent and contextually relevant responses to a wide range of prompts. Additionally, GPT-3.5 boasts impressive flexibility, enabling it to handle various tasks, from simple queries to complex creative writing projects. Its versatility and adaptability make it a valuable asset for idea generation and problem-solving across diverse domains, including process design.

In this study, we utilize the same case study as in our previous research (Mas'udah et al., 2021), where natural principles were integrated into the SDA framework to address diverse challenges. The case study pertains to enhancing the efficacy of the froth flotation process utilized in the extraction of nickel from pyrophyllite. Froth flotation is a process for selectively separating hydrophobic materials from hydrophilic ones (Maree et. al, 2017). Froth flotation is a very effective process for separating minerals, and it is used to recover a wide variety of minerals, including copper, lead, zinc, and gold. From a sustainability perspective, the use of chemical agents for nickel extraction poses a complex challenge. Fewer than 20 nickel mines globally resort to disposing of their waste in the sea, known as deep-sea tailings disposal (DSTD), impacting areas rich in coral reefs and diverse marine life. Companies often opt for DSTD due to cost efficiency or safety reasons, avoiding expenses related to tailings storage dams or waste treatment for ground reintegration. However, submarine tailings disposal is an outdated and harmful practice, causing severe harm to marine ecosystems and jeopardizing the livelihoods of fishing communities.

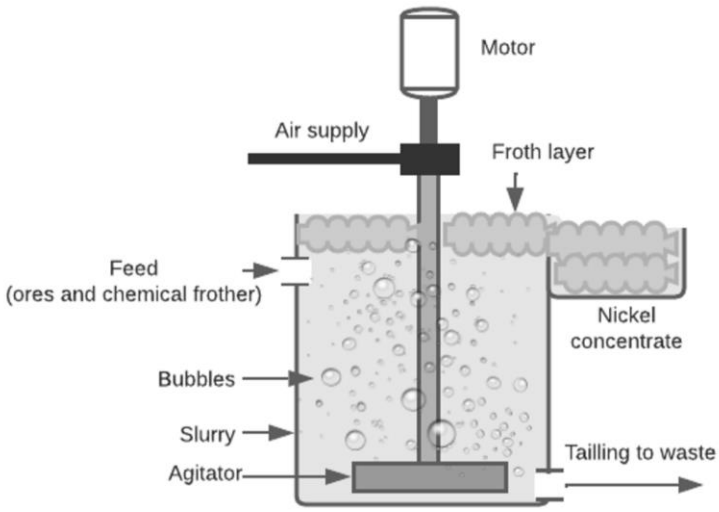

Figure 3. Froth flotation illustration for nickel recovery

To address these challenges, as illustrated in Figure 1, the methodology commences with the identification and examination of solutions derived from natural ecosystems. Various natural ecosystems in adverse environment were studied to uncover natural invention principles, similar to the approach taken in our recent study using the SDA method (Mas'udah et al., 2021). For instance, mangroves serve as a case study in this context (notwithstanding that mangroves are not the sole natural ecosystem applicable to specific problems in this study). Any natural ecosystem inhabiting unfavorable conditions can be considered for analysis. In the experimental phase, we utilized the same prompts for both GPT and Gemini. Applying two types of prompt design (basic and AI-automated prompting), we instructed the generative AI to analyse and extract natural principles from mangroves, then generate solution ideas to tackle the problems outlined in our case study. Each prompt setting was assigned to generate 10 ideas. In Table 4, we illustrate a comparison of the results from the ideas generation phase between GPT and Gemini, prompted with basic prompt.

Subsequently, the generated ideas were evaluated by both human experts and the AI itself, using the criteria specified in Table 2 above. The AI evaluation was conducted as a self-assessment by Gemini and ChatGPT3.5, evaluating their respective ideas. The human evaluation was carried out by the specialist team involved in the project's case study. In Table 4 here, we illustrate how Generative AI evaluates the solution ideas autonomously.

Table 3. Ideas generation with Basic prompt: GPT3.5 vs. Gemini (fragment)

Ideas generation phase

Prompt:
How to enhance the efficacy of the froth flotation process utilized in the extraction of nickel from pyrophyllite ores without causing secondary problems. ……………………………………………………………
Apply extracted natural inventive principles from mangrove tree components to generate the top 10 different ideas.

GPT 3.5

ChatGPT

Number	Short Idea Name	Short Description of the Idea
1	Segmented Collector Delivery	Utilize segmented delivery of collectors to ensure even distribution
2	Dynamic Air Injection	Implement dynamic air injection strategies to optimize bubble formation
3	Viviparous Collector Release	Introduce collectors gradually during the process, mimicking viviparous seed release
4	Salt Excretion Filtration	Employ salt excretion-like mechanisms to filter unwanted impurities
5	Thick Waxy Surface Coating	Develop a coating for hydrophobic minerals to mimic a thick waxy cuticle

Gemini

Number	Short Idea Name	Short Description of the Idea
1	Selective Filtration Membrane	Implement a selective filtration membrane to selectively separate nickel particles from the pyrophyllite ore without the need for chemical agents.
2	Multi-level Flotation System	Develop a multi-level flotation system that utilizes different air bubble sizes and flotation stages to selectively capture nickel particles based on their particle size and density.
3	Self-reliant Bio-surfactant Production	Cultivate a self-reliant bio-surfactant production system that utilizes microorganisms to produce natural surfactants specific to nickel particles, eliminating the need for chemical agents.

Ideas evaluation phase

Prompt:
Evaluate the generated ideas by assessing their feasibility, effectiveness, and potential for implementation. Use the following criteria to asses: …………………………………………..

GPT 3.5

ChatGPT
Sure, here's an evaluation of the ideas based on the provided criteria:

Number	Short Idea Name	Feasibility	Novelty	Usefulness	Overall Score
1	Segmented Collector Delivery	1	1	1	3
2	Dynamic Air Injection	1	1	2	4
3	Viviparous Collector Release	1	2	1	4
4	Salt Excretion Filtration	1	1	1	3
5	Thick Waxy Surface Coating	1	1	2	4
6	Prop Root-inspired Support	1	1	1	3
7	Pneumatophore-like Aeration	1	1	2	4
8	Self-Cleaning Froth Skimmer	1	2	2	5
9	Multifunctional Surfactants	1	1	2	4
10	Recyclable Collector	1	1	2	4

Gemini

Evaluation of Ideas for Enhanced Nickel Extraction

Number	Idea Name	Feasibility	Novelty	Usefulness	Notes
1	Selective Filtration Membrane	1	2	2	Existing membrane technologies might need adaptation, but promising for high selectivity.
2	Multi-level Flotation System	1	1	2	Requires engineering development but could improve separation efficiency.

Figure 4 depicts the comparison of the feasibility of solution ideas, highlighting significant differences in how humans and AI perceive the models' ability to complete tasks. Human evaluation indicates that GPT-3.5 and Gemini have nearly identical scores, suggesting that humans perceive both models as equally capable of task completion. In contrast, AI evaluation shows a more pronounced difference, with Gemini significantly outperforming GPT-3.5 in feasibility. This suggests that AI views Gemini as a model more adept at task completion. These differences may arise from AI's focus on aspects such as efficiency, accuracy, and resource utilization when assessing feasibility. Additionally, when employing

AI-automated prompting, Gemini excels in feasibility compared to GPT-3.5, indicating its ability to leverage complex and contextual instructions from AI to complete tasks more effectively.

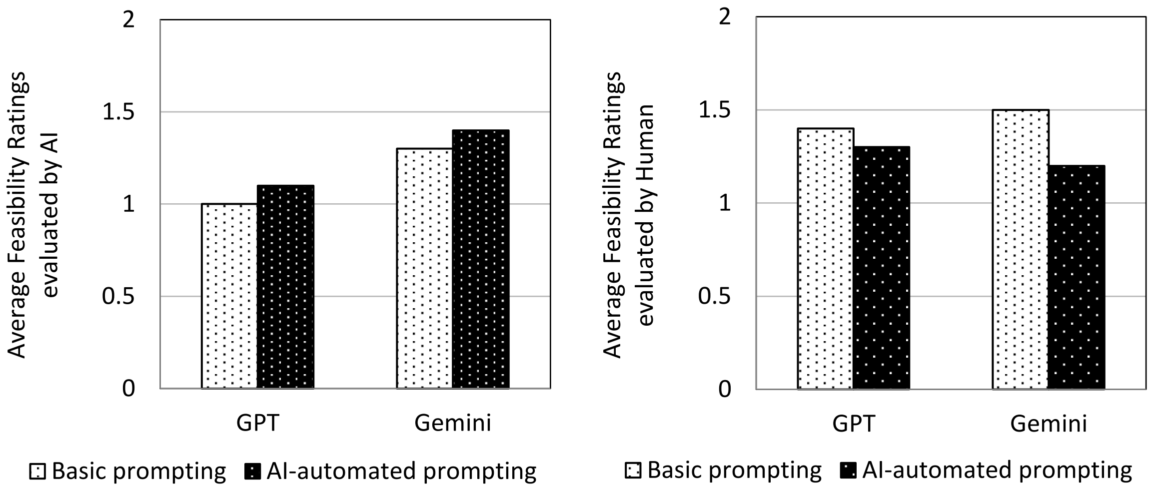

Figure 4. The average feasibility rating of generated ideas - between AI and human evaluation

Figure 5 illustrates the comparison of the novelty of solution ideas, indicating significant differences in how humans and AI perceive the originality and creativity of model outputs. Human evaluation shows similar ratings for both Gemini and GPT-3.5, suggesting that humans perceive both models as equally creative. However, AI evaluation reveals a notable gap, with Gemini outperforming GPT-3.5 in novelty. This discrepancy may arise from AI's ability to discern patterns and trends in data, enabling it to identify truly original outputs. Additionally, when utilizing AI-automated prompting, Gemini significantly surpasses GPT-3.5 in novelty, indicating its capacity to leverage complex and contextual instructions from AI to produce more original and creative outputs.

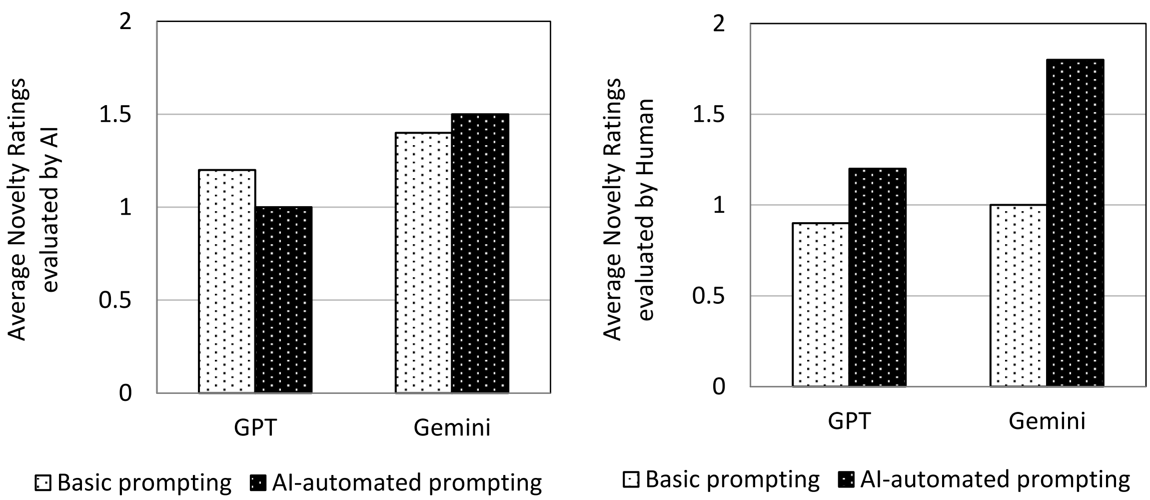

Figure 5. The average novelty rating of generated ideas - between AI and human evaluation

Figure 6 shows the comparison of the usefulness of solution ideas, revealing significant differences in how humans and AI perceive the benefit and value of model outputs. Human evaluation indicates that GPT-3.5 significantly outperforms Gemini in terms of usefulness, suggesting that humans view GPT's outputs as more beneficial and valuable compared to Gemini's. Conversely, AI evaluation demonstrates that Gemini significantly surpasses GPT-3.5 in usefulness, indicating that AI perceives Gemini's outputs as more beneficial and valuable. These differences may stem from AI's focus on aspects such as accuracy, relevance, and completeness of information when assessing usefulness. Additionally, when employing AI-automated prompting, Gemini outperforms GPT-3.5 in usefulness, highlighting its ability to leverage complex and contextual instructions from AI to produce outputs that are more beneficial and valuable.

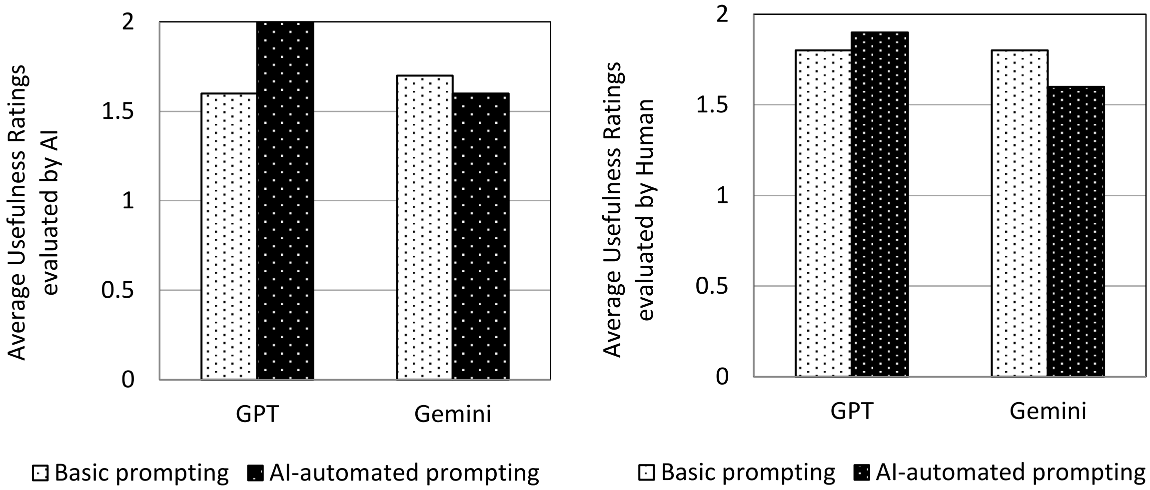

Figure 6. The average usefulness rating of generated ideas - between AI and human evaluation

In general, the evaluation of the feasibility, novelty and usefulness reveals significant differences in how AI and humans perceive language model capabilities. AI prioritizes efficiency, accuracy, and resource usage, while humans focus on simplicity and clarity. AI also emphasizes factors like sentence structure and word choice, whereas humans value uniqueness and originality. AI-automated prompts improve model performance by providing nuanced instructions. Gemini excels in novelty, reliability, and feasibility with AI-automated prompts, while GPT3.5 performs better in usefulness with basic prompts. Considering both AI and human perspectives is essential when selecting models.

4. Concluding remarks and outlook

Achieving sustainability is a high priority in process engineering. While traditional methods are valuable, they often face limitations and can be time-consuming, especially during the conceptual design phase to solve complex engineering challenges. Our overarching goal is to streamline the conceptual design process for engineers. This study investigates the integration of nature-inspired approaches with Large Language Models (LLMs) as a tool to suggest solutions for intricate engineering problems. Expert and AI evaluations were employed to assess differences. The findings indicate that with the right prompting strategies, LLMs can generate design solutions similar to those derived from conventional Solution-Driven Approach (SDA). By harnessing nature-inspired principles and Generative AI, this research showcases the potential of LLMs in mastering complex engineering tasks. Utilizing SDA models, Generative AI acts as a catalyst in addressing the multifaceted challenges in process engineering. Human and expert evaluations reveal that while LLM-generated solutions are more *feasible* and *useful*, they tend to be less *novel*. Despite promising outcomes, the methodologies used to generate solution ideas in this study require validation through practical implementation and rigorous evaluation to ensure real-world effectiveness. In addition, the strategies of natural ecosystem components identified by AI could not be translated into abstract inventive principles for engineering in the same way as we (humans) have done in our recent work (Mas'udah et al., 2023). Furthermore, the AI's analysis of the comprehensive interactions within the natural ecosystem often remained incomplete in our experiments. There are numerous opportunities to expand this work to support the creative aspects of early-stage conceptual design by using LLMs and nature-inspired principles to solve engineering problems.

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