

Prompt Engineering: a methodology for optimizing interactions with AI-Language Models in the field of engineering

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Abstract

ChatGPT is a versatile conversational Artificial Intelligence model that responds to user input prompts, with applications in academia and various sectors. However, crafting effective prompts can be challenging, leading to potentially inaccurate or contextually inappropriate responses, emphasizing the importance of prompt engineering in achieving accurate outcomes across different domains. This study aims to address this void by introducing a methodology for optimizing interactions with Artificial Intelligence language models, like ChatGPT, through prompts in the field of engineering. The approach is called GPEI and relies on the latest advancements in this area; and consists of four steps: define the objective, design the prompt, evaluate the response, and iterate. Our proposal involves two key aspects: data inclusion in prompt design for engineering applications and the integration of Explainable Artificial Intelligence principles to assess responses, enhancing transparency. It combines insights from various methodologies to address issues like hallucinations, emphasizing iterative prompt refinement techniques like posing opposing questions and using specific patterns for improvement. This methodology could improve prompt precision and utility in engineering.

Keywords: ChatGPT; prompt engineering; large language models; prompt design.

Ingeniería de instrucciones: una metodología para optimizar interacciones con Modelos de Lenguaje de IA en el campo de ingeniería

Resumen

ChatGPT es un modelo de Inteligencia Artificial conversacional versátil que responde a las indicaciones de entrada del usuario, con aplicaciones en el mundo académico y diversos sectores. Sin embargo, elaborar indicaciones efectivas puede ser un desafío, lo que lleva a respuestas potencialmente inexactas o contextualmente inapropiadas, lo que enfatiza la importancia de la ingeniería de instrucciones para lograr resultados precisos en diferentes dominios. Este estudio pretende abordar este vacío introduciendo una metodología para optimizar las interacciones con modelos de lenguaje de Inteligencia Artificial, como ChatGPT, a través de instrucciones en el campo de la ingeniería. El enfoque es llamado GPEI, y se basa en los últimos avances en esta área, el cual consta de cuatro pasos: definir el objetivo, diseñar el mensaje, evaluar la respuesta e iterar. Nuestra propuesta involucra dos aspectos clave: la inclusión de datos en el diseño rápido para aplicaciones de ingeniería y la integración de principios de Inteligencia Artificial Explicable para evaluar las respuestas, mejorando la transparencia. Combina conocimientos de varias metodologías para abordar problemas como las alucinaciones, enfatizando técnicas iterativas de refinamiento rápido, como plantear preguntas opuestas y usar patrones específicos para mejorar. Esta metodología podría mejorar la precisión y la utilidad rápidas en ingeniería.

Palabras clave: ChatGPT; ingeniería de instrucciones; grandes modelos de lenguaje; diseño de instrucciones.

1 Introduction

ChatGPT is the acronym for Chat Generative Pre-Trained Transformer, which can respond based on user requests using input text prompts [1]. As a conversational large language

model (LLM), ChatGPT has seen extensive applications across various sectors, including academia, and it can produce text that is often indistinguishable from that authored by humans [2,3]. ChatGPT is a generative AI platform that allows users to input text prompts, which generate responses

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based on the knowledge accumulated during the training phase [4]. Typical applications include text generation, summarization, and translation [5].

A prompt is a text describing a set of instructions that customize, refine, or enhance the capabilities of a GPT model [6]. Effective prompts are characterized by the following fundamental principles [7]: clarity and precision, contextual information, desired format, and verbosity control. However, writing effective prompts seems complicated for non-technical users, requiring creativity, intuition, and iterative refinement [7]. The problem becomes more significant when it is necessary to incorporate precise information to solve tasks in specific contexts.

Consequently, the answers can be vague, imprecise, factually incorrect, or contextually inappropriate [5] when an inadequate prompt is used. In this context, prompt engineering emerges as a discipline to design prompts by which users can program a Large Language Model, such as ChatGPT, to produce accurate answers [8,9].

During the last year, much gray literature has been generated that mainly presents prompt templates for specific workflows and tasks in marketing, advertising, SEO, and text translation. There are also many prompt templates for using these technologies in everyday tasks such as travel preparation. A quick analysis of this material allows us to conclude that the considerations made tend to be repetitive and need more depth to use these technologies as assistants in professional practice and engineering education. On the other hand, in the most relevant literature, efforts have been made to formalize the construction of prompts, as will be discussed later. However, research has concentrated mainly on practice, research, teaching, and scientific publication in health. Consequently, there is a gap when considering the opportunities of using GPT and conversational assistants in engineering; a similar conclusion is achieved in [10] by analyzing the potential uses of LLM in business process management.

This work seeks to fill this gap. We propose a methodology for developing prompts in engineering based on an iterative process based on the main developments that have been presented to date on this topic.

The rest of this work is organized as follows: Section 2 overviews the current discourse on GPT and prompt engineering. Section 3 presents the methodology employed to propose a framework for engineering prompts, elaborating and illustrating it further in Section 4. Finally, the paper is concluded in Section 5.

2 Literature review

Generative language models are part of the broader category of pre-trained Generative Transformers (GPT) and are part of deep learning models [11]. Their competence in interpreting and producing human language is based on the principles and techniques of natural language processing (NLP) [12]. The GPT approach is based on the principles of deep learning and NLP. Prompt engineering is essential to use generative language models effectively [13].

To evaluate generative language models, sentiment analysis and opinion mining are usually used, where users

rate their performance and express their opinions. This evaluation allows for continuous improvement of these systems. However, there are also profound ethical implications to its use, given its potential for disseminating biased or erroneous data and its implications for plagiarism and copyright [14,15]. In essence, generative language models offer substantial opportunities in various fields but require careful implementation, ethical oversight, and responsive adaptation to ensure their positive impact and reliability [16-19].

2.1 Discussion about ChatGPT

The current academic discussion about ChatGPT and LLM revolves around three axes: Generative Artificial Intelligence, Education, and Ethics.

Generative artificial intelligence (Generative AI), based on transformer architectures, is rapidly advancing in the domain of artificial intelligence [20,21]. These models can generate content in various formats, such as text, images, and more, that closely resemble what humans produce [20,21]. These elements profoundly impact professional practice and education [3,22]. Many concerns relate to academic and professional integrity and student evaluation [22,23]. The dual nature of technology (enabling academic dishonesty while potentially enriching pedagogical approaches) forces institutions to critically evaluate their assessment methodologies to ensure content accuracy and authenticity [22,23]. The foray of generative AI into the educational space has motivated academics to rethink traditional educational frameworks, generating opportunities and challenges [24,25]. In summary, the integration of generative artificial intelligence at the professional and academic levels requires rigorous evaluation, continuous research, and adaptation strategies to take advantage of its advantages and address the associated challenges [22-25].

Education is one of the areas most impacted by the popularization of GPTs, mainly by conversational agents powered by AI [26]. There are already many publications on this aspect in the most relevant literature, particularly for medical education. Since conversational models can generate human-like text, they can be used in curriculum design, as part of teaching methodologies, and to create personalized learning resources [26]. These capabilities facilitate the teaching of complex concepts and help educators monitor and refine their pedagogical approaches [26]. Beyond the educational field, conversational agents can offer relevant and accurate information to individuals and communities, thus demonstrating their usefulness as a complementary information resource that improves access to information and decision-making [14]. As in other cases discussed, there are essential concerns about possible bias, security, and ethical implications associated with using these tools [17,15]. For this reason, it is imperative to guarantee the accurate, transparent, and ethically sound deployment of these tools, especially for public consultation in general [16].

Models, such as ChatGPT, have generated immense interest due to their transformative potential in different sectors, such as administration, finance, health, and education [27]. However, their integration has raised complex

questions, particularly around authorship, plagiarism, and the distinction between human- and AI-generated content [27-29]. One of the fundamental issues is whether AI systems should be credited as authors in academic writings [27,28,30]. The distinction between human-written content and AI-generated content becomes more blurred, emphasizing concerns about plagiarism [27,28,31]. AI models can generate seemingly genuine but potentially misleading scientific texts [32]. In response, there is an emphasis on greater scrutiny, transparency, and ethical standards in using AI in research [31,32]. In this way, it is necessary to achieve a balance between the advantages of AI and ethical considerations becomes paramount [27,29,30,33], which requires an emphasis on transparency, fairness, and initiatives of open source [32,33].

2.2 Discussion about prompt engineering

Prompt engineering is a set of techniques and methods to design, write, and optimize instructions for LLM, called prompts, such that the model answers will be precise, concrete, accurate, replicable, and factually correct [8,9,18]. Prompts are understood as a form of programming because they can customize the outputs and interactions with an LLM [9]. They involve adapting instructions in natural language, obtaining the desired responses, guaranteeing contextually accurate results, and increasing the usefulness of generative language models in various applications [13]. Its applications include fields such as medical education, radiology, and science education [11,12,34]. These systems can be used, for example, as virtual assistants for student care or report writing, transforming complex information into a coherent narrative [11,26,34].

Efforts are underway to standardize the terminology and concepts within prompt engineering, with various classifications of prompts emerging based on different criteria.

According to the structure, prompts can be formulated using open-ended or closed-ended questions. Open-ended questions do not have a specific or limited answer and allow for a more extensive and detailed response from the model. They are helpful, for example, for critical reading tasks [35]. In contrast, closed-ended questions typically have specific and limited answers, often yes or no, multiple-choice, or a short and defined response. For example, instead of asking “*What is the capital of Italy?*” (close-ended question), an open-ended question might be, “*Tell me about the history and culture of Rome.*”

According to the information provided, prompts can be categorized into levels 1 to 4. The first level consists of straightforward questions, while the second level introduces additional context about the writer and the language model. The third level includes provided examples for the language model to reference, and the fourth level allows the language model to break down the request into individual components (much like requesting a step-by-step solution to a mathematical problem, offering the language model a more structured way to handle the prompt for improved accuracy) [36].

Comparably, prompts have also been classified as instructive, system, question-answer, and mixed. Instructive

prompts start with a verb that specifies the action to be performed by the system. System prompts provide the system with a starting point or context to develop content. Question-answer prompts formulate a wh* type question. Mixed prompts blend two or more techniques mentioned above [8].

According to the number of examples provided, instructions are classified as zero-shot and few-shot prompts, where “shot” is equivalent to an example [36]. Zero-shot prompts are used in situations where it is not necessary to train the LLM or present sample outputs [37]. Examples of zero-shot prompts include prompts used to translate or summarize texts; other examples of zero-shot prompts are simple questions that are answered with the internal knowledge of the LLM, such as, for example, “define prompt engineering.” Few-shot prompts cover prompts with more detailed information.

Reproducibility is a desired characteristic, but LLM produces an inherent random response due to its intrinsic design [7].

Many sources recognize that the development of prompts is an iterative process. Also, it is desired that the prompt text must be clear, concise, and to the point, avoiding unnecessary complexity [38].

Following the discussion, poorly designed prompts generate vague, biased, misleading, or ambiguous responses. Another major problem is hallucinations [5,9]. Many researchers highlight the necessity of verifying facts presented in the response of conversational LLMs, such as academic citations.

3 Methodology

We conducted a comprehensive literature search using the Scopus database to identify scientific papers on prompt engineering. Scopus is renowned as one of the largest repositories of peer-reviewed scientific literature, and it encompasses a broad spectrum of disciplines, including science, technology, medicine, and social sciences [39].

We designed and used the following search equation, which retrieved 184 documents.

```
TITLE ( ( prompt AND ChatGPT ) OR ( prompt AND
engineering ) ) OR KEY ( ( prompt AND ChatGPT ) OR (
prompt AND engineering ) )
```

The analysis of the documents and the valuable findings for a prompt design methodology are presented below.

4 Results

4.1 Analysis

The majority of the literature found can be categorized into two groups: specific applications (particularly in the field of medicine) and guidelines and recommendations for prompt design [36] [38]. Only seven papers go beyond prompt design to propose a methodology for interacting with

Table 1.
Components of methodologies.

Authors	Application	Guidelines	Data	Evaluation Criteria	Iteration
Chang (2023) [35]	Critical Reading	X		X	X
Eager and Brunton, 2023 [18]	Education	X	X	X	X
Giray, 2023 [8]	Academic Writing	X	X		
Jha et al., 2023 [5]	General			X	X
Lo, 2023 [19]	General	X		X	X
Shieh, 2023 [40]	General				X

Source: The authors

chatGPT using prompts. This situation can be attributed to the large number of documents and gray literature offering compilations of prompt examples and templates for specific tasks such as marketing, advertising, or text translation. These guides are designed for the non-technical user, and they play an essential role in popularizing ChatGPT and LLM, although they may not be part of the scientific literature. Table 1 presents the components of these methodologies and other pertinent sources within the gray literature.

Several methodologies have been developed for general applications (though they are typically published in medical field journals), while some have been proposed for specific domains. We did not find any methodologies proposed for the field of engineering.

Most of the methodologies provide guidelines for prompt design and incorporate interactivity. However, given the nature of the application field, some methodologies are based on specific prompt designs, such as open-ended questions for critical reading [35] or persona design for academic writers [8]. Only two methodologies include providing data within the prompt for the system's response retrieval.

While some methodologies involve evaluating the response before iterating on the prompt [5,18,19,35], not all of them provide components for conducting this assessment [5,18].

Even though some methodologies hold promise, they are not currently directly applicable to prompt design. For instance, in [5,41], a methodology is proposed that may be useful for the internal programming of LLMs but not for human-user interaction with such systems. Furthermore, in [42], a hermeneutic exercise is conducted without a proposed methodology that can be applied to other domains.

As of the publication date of this paper, we have not found official documentation from Google on recommendations for interacting with Bard (the Artificial Intelligence system developed by the company [43]). Similarly, we have not come across official documentation from Microsoft regarding recommendations for interacting with 12hatGPT through their Bing browser [44].

4.1 Proposal

We collected the guidelines, recommendations, and common elements from the various methodologies for prompt design that were analyzed earlier. Furthermore, we also considered issues related to hallucinations and low-quality responses and integrated those elements into a

methodology for interacting with ChatGPT through prompts for the engineering field.

The methodology is called GPEI, which stands for Goal Prompt Evaluation Iteration. GPEI consists of 4 steps: (1) define a goal, (1) design the prompt, (3) evaluate the answer, and (4) iterate, as Figure 1 shows. The methodology is explained below.

4.2.1. Step 1: Define a goal

The process begins by defining the goal to be achieved by the AI model. The goal will determine the structure of the prompt to be designed in the following step and assist in evaluating the quality of the system's response before further iterations. Despite its significance, this activity is explicitly outlined only in one of the analyzed methodologies [18]; in the remaining methodologies, the objective is disaggregated within the prompt design.

4.2.2. Step 2: Prompt designing

The first step consists of the design of the prompt. In [9], a catalog of prompt patterns is presented and discussed. The authors describe 12 patterns for prompt designing; also, they identify for each pattern the intent, motivation, key ideas, and consequences of the approach. Five of these patterns are oriented toward customizing the output obtained from the system: output Automater, persona, visualization generator, recipe, and template.

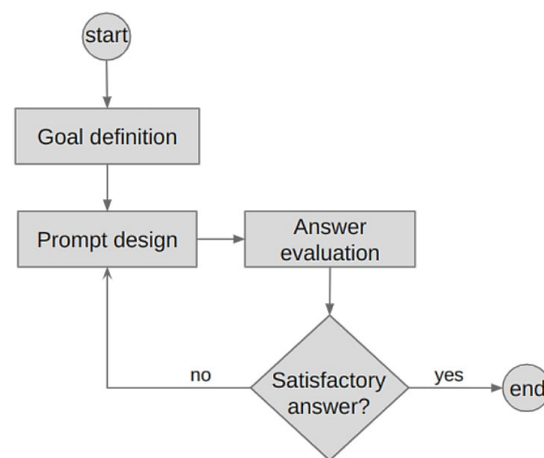


Figure 1. GPEI Methodology
Source: The authors.

I am profiling a bibliographic dataset for writing a literature review paper. You are an automatic writer assistant. The table below, delimited by triple backticks, provides data on the main characteristics of the records and fields of the bibliographic dataset. Your task is to generate a short paragraph with conclusions by using the information in the table. Limit your description to one paragraph in at most 100 words.

Table:
 ```  
 [Data here]  
 ```

Figure 2. Example of a prompt template for including specific information. Source: The authors.

According to the established goal, the user should use the pattern that best suits their purpose. For example, if the persona pattern is chosen, the prompt should have the following elements [36]:

- The definition of the role of the person who is asking the question.
- The definition of a role or a context: "you are ...", "you act as ..."
- The definition of what is required: Your task is ... / Write ... / Rephrase ... /
- A description of the output format (for example, a paragraph, a bulleted list, a table, JSON data, etc).
- A description of limits for the expected results.

In an engineering context, we advise that the prompt includes the necessary data for the system to generate responses. An example is presented in Fig. 2.

The literature provides some recommendations for prompt design.

- Extending prompts with phrases such as "within the scope" and "Let's think step by step ... to reach conclusions" could improve the response of the system.
- A strategy for complex responses involves asking LLM to break the result into small chunks [45].
- Think that prompts are instructions in the context of computer programming, such that it is unnecessary to be polite; avoid phrases such as "Please, give me ..." [45].
- Strategies, such as the Tree of Thoughts [41], can be used to structure prompts for complex problems.
- Frameworks, such as CLEAR, propose a Concise, Logical, Explicit, Adaptive, and Reflective process to optimize interactions with AI language models like ChatGPT through prompts.
- OpenAI suggests separating instructions from the context through a break in the prompt or using quotation marks to reference textual elements from the context [40].
- Adding examples to articulate the desired output could also be useful [40].

Moreover, the prompt can be used as a template for solving similar problems or generating new prompts for similar problems (template pattern [9]). Disambiguation can be avoided by providing a detailed description or scope of the problem or the data, as exemplified in Fig. 3.

A more comprehensive guide for developing template prompts can be found in [35]. A very important recommendation is to use the designed prompt in the chat and then collect and save

the system output. At this point, it is imperative to preserve the history of the process design to realize ex-post evaluations of the performance of the designed prompts.

4.2.3. Step 3: Evaluate the answer.

Realize a formal verification of the answer provided by ChatGPT in terms of the design criteria specified in Step 1. Evaluating the obtained response is not trivial since it can potentially reduce system hallucination.

The following questions could be helpful in this purpose [19]:

Is the answer as complete as expected?

Is the answer as accurate as expected?

Is the answer as relevant as expected?

Were the specified limits met?

Does the answer have elements that may be factually incorrect (hallucinations)?

Does the answer have elements that may be contextually inappropriate?

The available literature offers various methods for assessing ChatGPT's responses. For instance, one approach involves rephrasing a question to elicit different responses, which can help identify inconsistencies among multiple answers. Additionally, requesting additional evidence, such as querying top-k information sources and having the language model rate the credibility of each source, is another strategy. Also, one can seek opposing viewpoints from the language model, including their sources and credibility, to evaluate the strength of a different perspective [35]. It is also possible.

In [5], formal methods are integrated into the design of prompts for critical and autonomous systems with the aim of self-monitoring and automatic detection of errors and hallucinations. Among the recommendations, the authors suggest that one could consider providing counterexamples in the prompt to prevent hallucinations [5].

Furthermore, it is possible to design other prompts to evaluate a response. For instance, prompts falling under the *error identification* category in [9] involve generating a list of facts the output depends on that should be fact-checked and then introspecting on its output to identify any errors.

A potentially useful strategy to evaluate the answer of an LLM is to incorporate elements commonly used to design Explainable AI systems (XAI) [46]. We propose the following guidelines to incorporate these principles to evaluate the answer's quality:

I am working on a guideline for design prompts for LLM. You are an automatic writer assistant. Your task is to generate a short paragraph defining what prompt engineering is. The text below, delimited by '<<<' and '>>>', provides several paragraphs defining what is prompt engineering. Use only the provided text to write a paragraph defining prompt engineering. Limit your description to one paragraph in at most 100 words.

Here is the text:
 <<<
 [Insert the text here]
 >>>

Figure 3. Prompt example for including specific information. Source: The authors.

- Ask for the reasoning behind a particular answer.
- Verify that the prompt asking the LLM provides a simple, direct, and unambiguous response.
- Verify the prompt requires the LLM to justify the answer.
- Ask the LLM to break down the answer in bullets, steps, or stages for complex answers.
- Inquire about the data sources or training data.

4.2.4. Step 4: Iterate

If the answer fails to meet the evaluation criteria, prompt modification is required, which entails adjusting the design obtaining and assessing a new answer. This iterative refinement process continues until the system's response is deemed adequate.

As suggested in [35], the iterative process could be as simple as posing the same question from an opposing perspective. However, other strategies that use specific prompt patterns can also be helpful, like the patterns within the *improvement group* focus on enhancing the quality of both input and output. Patterns in this category involve suggesting alternative ways for the Language Model (LLM) to accomplish a user-specified task, instructing the LLM to automatically propose a series of subquestions for users to answer before combining these subquestion answers to produce a response to the overarching question (similar to [41]) and mandating the LLM to automatically rephrase user queries when it declines to provide an answer.

Moreover, the utilization of particular prompt patterns can prove advantageous. For example, patterns found within the *Improvement* category in [9] focus on enhancing input and output quality. These patterns suggest alternative methods for the LLM to execute a task specified by the user, directing the LLM to autonomously present a sequence of subquestions for users to address before amalgamating these subquestion responses to formulate a comprehensive answer to the primary inquiry. Additionally, they instruct the LLM to automatically rephrase user queries in cases where it refuses to produce a solution.

4.2 Application

For this example, we will seek the solution to a well-known engineering problem: the knapsack problem [47]. In this problem, one must decide which items to take on a trip based on the utility value of each item, the weight of each item, and a limit on the total weight that can be carried.

4.3.1. Step 1: Define a goal.

From a given list of items, one should find the combination that has the highest total benefit without exceeding a total weight of 10 kg.

4.3.2. Step 2: Design the prompt.

The designed prompt and the corresponding response are presented in Table 2.

Table 2.

First iteration for the application case.

Role	Dialogue
Prompt	Given the items below, choose the set of items that has the highest total value, as long as the sum of the weights of those items does not exceed 10 kilograms: Item 1: Value - 8, Weight - 3 kg; Item 2: Value - 6, Weight - 2 kg; Item 3: Value - 10, Weight - 5 kg; Item 4: Value - 3, Weight - 1 kg; Item 5: Value - 7, Weight - 4 kg; Item 6: Value - 9, Weight - 3 kg; Item 7: Value - 5, Weight - 2 kg; Item 8: Value - 4, Weight - 1 kg; Item 9: Value - 2, Weight - 6 kg; Item 10: Value - 10, weight - 10 kg
GPT	Given the items provided, the optimal selection to achieve the highest total value without exceeding 10 kilograms would be: * Item 1: Value - 8, Weight - 3 kg * Item 2: Value - 6, Weight - 2 kg * Item 3: Value - 10, Weight - 5 kg * Total value: 24; Total weight: 10 kg

Source: The authors.

Table 3.

Second iteration for the application case.

Role	Dialogue
Prompt	Given the items below, give me three sets with the highest total value. The sets can have any number of elements as long as they are not repeated, and the sum of the weights of those items does not exceed 10 kilograms. Show only sets that do not exceed 10 kilograms: Item 1: Value - 8, Weight - 3 kg; Item 2: Value - 6, Weight - 2 kg; Item 3: Value - 10, Weight - 5 kg; Item 4: Value - 3, Weight - 1 kg; Item 5: Value - 7, Weight - 4 kg; Item 6: Value - 9, Weight - 3 kg; Item 7: Value - 5, Weight - 2 kg; Item 8: Value - 4, Weight - 1 kg; Item 9: Value - 2, Weight - 6 kg; Item 10: Value - 10, weight - 10 kg; Your best answer has been: Item 1: Value - 8, Weight - 3 kg; Item 2: Value - 6, Weight - 2 kg; Item 3: Value - 10, weight - 5 kg
GPT	Given the items provided and the constraint that the total weight cannot exceed 10 kilograms, here are three sets with the highest total value that do not exceed the weight limit: Set 1: * Item 3: Value - 10, Weight - 5 kg * Item 6: Value - 9, Weight - 3 kg. * Item 1: Value - 8, Weight - 3 kg. Total Value: 27 Total Weight: 11 kg (exceeds weight limit) Set 2: * Item 3: Value - 10, Weight - 5 kg * Item 2: Value - 6, Weight - 2 kg * Item 1: Value - 8, Weight - 3 kg Total Value: 24 Total Weight: 10 kg (within weight limit); Set 3: * Item 3: Value - 10, Weight - 5 kg * Item 6: Value - 9, Weight - 3 kg * Item 2: Value - 6, Weight - 2 kg Total Value: 25 Total Weight: 10 kg (within weight limit). These sets provide the highest total value without exceeding the 10 kilograms weight limit.

Source: The authors.

4.3.3. Step 3: Evaluate the answer.

The items meet the imposed restriction; however, when independently verified using an optimization tool, the following is the optimal solution:

- Item 1: Value - 8, Weight - 3 kg.
- Item 2: Value - 6, Weight - 2 kg.
- Item 4: Value - 3, Weight - 1 kg.
- Item 6: Value - 9, Weight - 3 kg.
- Item 8: Value - 4, Weight - 1 kg.
- Total value: 30.
- Total weight: 10 kg

Let's see if we can find a better solution than the one found in iteration 1 using ChatGPT.

4.3.4. Step 4: Iterate

A new designed prompt, presented in Table 3, is used for the second iteration. Although a better answer was achieved in this iteration than the previous one, ChatGPT still does not find the system's optimum. Other strategies will be employed in iterations 3 and 4 to aid in solving this problem.

For the iteration 3, the strategy is changed from asking for the solution to requesting the formulation of the problem (See Table 4). In the iteration 4, we designed a prompt to request the generation of the code necessary for Google Collaboratory [48] to solve the previous problem. The dialogue is presented in Table 5.

Table 4.
Iteration 3 for the application case.

Role	Dialogue
Prompt	<p>Formulate the objective function and the correspondent constraints for the following problem:</p> <p>Given a number of items, each characterized by a value and a weight in kilograms, find the set of items where the sum of their values is maximum, and the sum of their weights is less than or equal to 10 kilograms. The sets can have any number of elements, as long as they are not repeated.</p>
GPT	<p>This is a classic Knapsack problem.</p> <p>Objective function:</p> <p>Maximize Z where:</p> $Z = \sum_{i=1}^n w_i x_i \leq 10$ <p>This objective function represents the total value of the selected items.</p> <p>Constraints:</p> <p>1. The total weight of the selected items should not exceed 10 kg:</p> $\sum_{i=1}^n w_i x_i \leq 10$ <p>2. Decision variable constraints:</p> $0 \leq x_i \leq 1$ <p>and x_i must be an integer (binary)</p> <p>The objective function aims to maximize the total value of selected items, subject to the constraints that the total weight does not exceed 10 kilograms and each item is either selected or not and not repeated.</p>

Source: The authors.

Table 5.
Iteration 4 for the application case.

Role	Dialogue
Prompt	<p>Generate a code to solve this problem for Google Colab, Use the following items for the code: Item 1: Value - 8, Weight - 3 kg; Item 2: Value - 6, Weight - 2 kg; Item 3: Value - 10, Weight - 5 kg; Item 4: Value - 3, Weight - 1 kg; Item 5: Value - 7, Weight - 4 kg; Item 6: Value - 9, Weight - 3 kg; Item 7: Value - 5, Weight - 2 kg; Item 8: Value - 4, Weight - 1 kg; Item 9: Value - 2, Weight - 6 kg; Item 10: Value - 10, weight - 10 kg</p>
GPT	<pre># Import PuLP library !pip install pulp from pulp import (LpMaximize, LpProblem, lpSum, LpVariable) prob = LpProblem("Maximize_Value", LpMaximize) items = { 1: {"value": 8, "weight": 3}, 2: {"value": 6, "weight": 2}, 3: {"value": 10, "weight": 5}, 4: {"value": 3, "weight": 1}, 5: {"value": 7, "weight": 4}, 6: {"value": 9, "weight": 3}, 7: {"value": 5, "weight": 2}, 8: {"value": 4, "weight": 1}, 9: {"value": 2, "weight": 6}, 10: {"value": 10, "weight": 10} } item_vars = LpVariable.dicts("Item", items.keys(), 0, 1, LpVariable) prob += lpSum(item_vars[i] * items[i]["value"] for i in items) prob += lpSum(item_vars[i] * items[i]["weight"] for i in items) <= 10 prob.solve() selected_items = [i for i in items if item_vars[i].value() == 1] total_value = sum(items[i]["value"] for i in selected_items) total_weight = sum(items[i]["weight"] for i in selected_items) print("Selected items:") for i in selected_items: print(f"Item {i}: " f"Value - {items[i]['value']}, " f"Weight - {items[i]['weight']} kg") print(f"Total Value: {total_value}") print(f"Total Weight: {total_weight} kg")</pre>

Source: The authors.

When we ran the code in Google Colab, we obtained this response:

```
Requirement      already      satisfied:      pulp      in
/usr/local/lib/python3.10/dist-packages (2.7.0)
Selected items:
Item 1: Value - 8, Weight - 3 kg;
Item 2: Value - 6, Weight - 2 kg;
Item 4: Value - 3, Weight - 1 kg;
Item 6: Value - 9, Weight - 3 kg;
```

Item 8: Value - 4, weight - 1 kg;
 Total Value: 30;
 Total Weight: 10 kg

Which is the correct solution to the problem. So here, we halted the process.

5 Conclusions

Prompt engineering plays a pivotal role in optimizing the performance of LLM by crafting instructions or prompts that elicit precise, accurate, and contextually appropriate responses. Designing effective prompts is iterative and requires clear and concise language to avoid generating vague or biased responses.

A literature analysis found that multiple methodologies for prompt engineering have been developed. Notably, no methodologies were found specifically designed for engineering. Most of these methodologies offer guidance for prompt design and emphasize iterative processes. Only two methodologies include data within the prompt to facilitate system response retrieval. While some methodologies involve response evaluation before iterating on the prompt, not all of them provide components for this assessment.

We propose an iterative methodology for optimizing interactions with AI language models in engineering through prompts named GPEI. It is a four-step process, including defining a goal, designing the prompt, evaluating the answer, and iterating to achieve an adequate response. GPEI has two key elements: the inclusion of data in prompt design, making it suitable for applications in the field of engineering, and the inclusion of principles from Explainable AI (XAI) systems to evaluate answers is proposed, promoting transparency and justifiability in the responses generated by LLM.

Our methodology integrates guidelines, recommendations, and common elements from various methodologies to address issues like hallucinations and low-quality responses. The iterative nature of prompt refinement is emphasized, with suggestions such as asking opposing questions and using specific prompt patterns for improvement. This methodology is a valuable tool for designing prompts in engineering.

The application example showcased the capabilities of chatGPT in addressing engineering problems when integrated with other calculation tools. Future work stemming from this research is related to applying the methodology in various engineering applications to incorporate the necessary enhancements for improving its utility.

References

- [1] Lund, B.D., Wang, T., Mannuru, N.R., Nie, B., Shimray, S., and Wang, Z., ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing, *J. Assoc. Inf. Sci. Technol.*, 74(5), pp. 570-581, 2023. DOI: <https://doi.org/10.1002/asi.24750>.
- [2] Macdonald, C., Adeloje, D., Sheikh, A., and Rudan, I., Can ChatGPT draft a research article? An example of population-level vaccine effectiveness analysis, *J. Glob. Health*, 13, 2023. DOI: <https://doi.org/10.7189/JOGH.13.01003>.
- [3] Rudolph, J., Tan, S., and Tan, S., ChatGPT: bullshit spewer or the end of traditional assessments in higher education? *J. Appl. Learn. Teach.*, 6(1), pp. 342-363, 2023. DOI: <https://doi.org/10.37074/jalt.2023.6.1.9>.
- [4] Pavlik, J.V., Collaborating with ChatGPT: considering the implications of generative artificial intelligence for journalism and media education, *Journal. Mass Commun. Educ.*, 78(1), pp. 84-93, 2023. DOI: <https://doi.org/10.1177/10776958221149577>.
- [5] Jha, S., Jha, S.K., Lincoln, P., Bastian, N.D., Velasquez, A., and Neema, S., Dehallucinating large language models using formal methods guided iterative prompting, in: 2023 IEEE International Conference on Assured Autonomy (ICAA), IEEE, 2023. pp. 149-152.
- [6] Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., and Neubig, G., Pre-train, prompt, and predict: a systematic survey of prompting methods in natural language processing, *ACM Comput. Surv.*, 55(9), pp. 1-35, 2023.
- [7] Lo, L.S., The art and science of prompt engineering: a new literacy in the information age, *Internet Ref. Serv. Q.*, 2023. DOI: <https://doi.org/10.1080/10875301.2023.2227621>.
- [8] Giray, L., Prompt engineering with ChatGPT: a guide for academic writers, *Ann. Biomed. Eng.*, 2023. DOI: <https://doi.org/10.1007/s10439-023-03272-4>.
- [9] White, J. et al., A prompt pattern catalog to enhance prompt engineering with chatgpt, *ArXiv Prepr. ArXiv230211382*, 2023.
- [10] Busch, K., Rochlitzer, A., Sola, D., and Leopold, H., Just tell me: prompt engineering in business process management, in: *International Conference on Business Process Modeling, Development and Support*, Springer, 2023, pp. 3-11.
- [11] Lecler, A., Duron, L., and Soander, P., Revolutionizing radiologand with GPT-based models: current applications, future possibilities and limitations of ChatGPT, *Diagn. Interv. Imaging*, 104(6), pp. 269-274, 2023. DOI: <https://doi.org/10.1016/j.diii.2023.02.003>.
- [12] Eandsenbach, G., The role of ChatGPT, generative language models, and artificial intelligence in medical education: a conversation with ChatGPT and a call for papers, *JMIR Med. Educ.*, 9, 2023. DOI: <https://doi.org/10.2196/46885>.
- [13] Wu, T., Terrand, M., and Cai, C.J., AI chains: transparent and controllable Human-AI interaction band chaining large language model prompts, in: *Conference on Human Factors in Computing Sandstems - Proceedings*, 2022. DOI: <https://doi.org/10.1145/3491102.3517582>.
- [14] Raand P.P., and Majumder, P., Assessing the Accuracand of responses band the language model ChatGPT to questions regarding bariatric surgerand: a critical appraisal, *Obes. Surg.*, 33(8), pp. 2588-2589, 2023. DOI: <https://doi.org/10.1007/s11695-023-06664-6>.
- [15] Gupta, R., Herzog, I., Weisberger, J., Chao, J., Chaianasate, K., and Lee, E.S., Utilization of ChatGPT for plastic surgerand research: friend or foe?, *J. Plast. Reconstr. Aesthet. Surg.*, 80, pp. 145-147, 2023. DOI: <https://doi.org/10.1016/j.bjps.2023.03.004>.
- [16] Deiana, G., Dettori, M., Arghittu, A., Azara, A., Gabutti, G., and Castiglia, P., Artificial intelligence and public health: evaluating ChatGPT responses to vaccination mandths and misconceptions, *Vaccines*, 11(7), art. 11071217, 2023. DOI: <https://doi.org/10.3390/vaccines11071217>.
- [17] Corsello, A. and Santangelo, A., Maand artificial intelligence influence future pediatric research?—The case of ChatGPT, *children*, 10(4), 2023. DOI: <https://doi.org/10.3390/children10040757>.
- [18] Eager, B., and Brunton, R., Prompting higher education towards AI-Augmented teaching and learning practice, *J. Univ. Teach. Learn. Pract.*, 20(5), 2023. DOI: <https://doi.org/10.53761/1.20.5.02>.
- [19] Lo, L.S., The CLEAR path: a framework for enhancing information literacand through prompt engineering, *J. Acad. Librariansh.*, 49(4), 2023. DOI: <https://doi.org/10.1016/j.acalib.2023.102720>.
- [20] DK. Dwivedi, et al., So what if ChatGPT wrote it? Multidisciplinarand perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policand, *Int. J. Inf. Manag.*, 71, 2023. DOI: <https://doi.org/10.1016/j.ijinfomgt.2023.102642>.
- [21] Harrer, S., Attention is not all andou need: the complicated case of ethicalland using large language models in healthcare and medicine, *eBioMedicine*, 90, 2023. DOI: <https://doi.org/10.1016/j.ebiom.2023.104512>.
- [22] Crawford, J., Cowling, M., and Allen, K.-A., Leadership is needed for ethical ChatGPT: character, assessment, and learning using artificial

- intelligence (AI), *J. Univ. Teach. Learn. Pract.*, 20(3), 2023. DOI: <https://doi.org/10.53761/1.20.3.02>.
- [23] Alexander, K., Savvidou, C., and Alexander, C., Who wrote this essay? Detecting ai-generated writing in second language education in higher education, *Teach. Engl. Technol.*, 23(2), pp. 25-43, 2023. DOI: <https://doi.org/10.56297/BUKA4060/XHLD5365>.
- [24] Lim, W.M., Gunasekara, A., Pallant, J.L., Pallant, J.I., and Pechenkina, E., Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators, *Int. J. Manag. Educ.*, 21(2), 2023, DOI: <https://doi.org/10.1016/j.ijme.2023.100790>.
- [25] Bilal, M., Jamil, Y., Rana, D., and Shah, H.H., Enhancing awareness and Self-diagnosis of obstructive sleep apnea using AI-Powered chatbots: the role of ChatGPT in revolutionizing healthcare, *Ann. Biomed. Eng.*, 2023. DOI: <https://doi.org/10.1007/s10439-023-03298-8>.
- [26] Epstein, R.H., and Dexter, F., Variability in large language Models' responses to medical licensing and certification examinations. comment on "How Does ChatGPT Perform on the United States Medical Licensing Examination? The Implications of Large Language Models for Medical Education and Knowledge Assessment", *JMIR Med. Educ.*, 9, 2023. DOI: <https://doi.org/10.2196/48305>.
- [27] Marchandot, B., Matsushita, K., Carmona, A., Trimaille, A., and Morel, O., ChatGPT: the next frontier in academic writing for cardiologists or a Pandora's box of ethical dilemmas, *Eur. Heart J. Open*, 3(2), 2023. DOI: <https://doi.org/10.1093/ehjopen/oead007>.
- [28] Graf, A. and Bernardi, R.E., ChatGPT in research: balancing ethics, transparency and advancement, *Neuroscience*, 515, pp. 71-73, 2023. DOI: <https://doi.org/10.1016/j.neuroscience.2023.02.008>.
- [29] Yan, D., Impact of ChatGPT on learners in a L2 writing practicum: an exploratory investigation, *Educ. Inf. Technol.*, 2023. DOI: <https://doi.org/10.1007/s10639-023-11742-4>.
- [30] Ruksakulpiwat, S., Kumar, A., and Ajibade, A., Using ChatGPT in Medical research: current status and future directions, *J. Multidiscip. Healthc.*, 16, pp. 1513-1520, 2023. DOI: <https://doi.org/10.2147/JMDH.S413470>.
- [31] Májovský, M., Černý, M., Kasal, M., Komarc, M., and Netuka, D., Artificial intelligence can generate fraudulent but authentic-looking scientific medical articles: Pandora's box has been opened, *J. Med. Internet Res.*, 25, 2023. DOI: <https://doi.org/10.2196/46924>.
- [32] Spirling, A., When open-source generative AI models are an ethical wall forward for science, *nature*, 616(7957), art. 413, 2023. DOI: <https://doi.org/10.1038/d41586-023-01295-4>.
- [33] Wang, S.H., OpenAI — explain when some countries are excluded from ChatGPT, *nature*, 615(7950), art. 34, 2023. DOI: <https://doi.org/10.1038/d41586-023-00553-9>.
- [34] Cooper, G., Examining science education in ChatGPT: An exploratory study of generative artificial intelligence, *J. Sci. Educ. Technol.*, 32(3), pp. 444-452, 2023. DOI: <https://doi.org/10.1007/s10956-023-10039-and>.
- [35] Chang, E.Y., Prompting large language models with the Socratic method, in: 2023 IEEE 13th Annual Computing and Communication Workshop and Conference, CCWC 2023, 2023, pp. 351-360. DOI: <https://doi.org/10.1109/CCWC57344.2023.10099179>.
- [36] Heston, T.F., and Khun, C., Prompt engineering in medical education, *Int. Med. Educ.*, 2(3), pp. 198-205, 2023.
- [37] Yong, G., Jeon, K., Gil, D., and Lee, G., Prompt engineering for zero-shot and few-shot defect detection and classification using a visual-language pretrained model, *Comput.-Aided Civ. Infrastruct. Eng.*, 38(11), pp. 1536-1554, 2023. DOI: <https://doi.org/10.1111/mice.12954>.
- [38] Bozkurt, A., and Sharma, R.C., Generative AI and prompt engineering: the art of whispering to let the genie out of the algorithmic world, *Asian J. Distance Educ.*, 2023.
- [39] Elsevier, When choose Scopus - Scopus benefits. [online]. Accessed: July 31st of 2020. Available at: <https://www.elsevier.com/solutions/scopus/when-choose-scopus>
- [40] Shieh, J., Best practices for prompt engineering with OpenAI API, OpenIA, [online]. Sept. 2023. Accessed: October 3rd of 2023. Available at: <https://help.openai.com/en/articles/6654000-best-practices-for-prompt-engineering-with-openai-api>
- [41] Yao, S. et al., Tree of thoughts: deliberate problem solving with large language models, *ArXiv Prepr. ArXiv230510601*, 2023.
- [42] Henrickson, L., and Meroño-Peñuela, A., Prompting meaning: a hermeneutic approach to optimising prompt engineering with ChatGPT, *AI Soc.*, 2023, DOI: <https://doi.org/10.1007/s00146-023-01752-8>.
- [43] Google, Bard - Chat based AI tool from Google, powered by PaLM 2. [online]. Accessed: October 4th of 2023. Available at: <https://bard.google.com>
- [44] Microsoft, Your AI-Powered Copilot for the Web | Microsoft Bing. [online]. Accessed: October 4th of 2023. Available at: <https://www.microsoft.com/en-us/bing>
- [45] Spasic, A.J., and Jankovic, D.S., Using ChatGPT standard prompt engineering techniques in lesson preparation: role, instructions and seed-word prompts, in: 2023 58th International Scientific Conference on Information, Communication and Energy and Sandstems and Technologies, ICEST 2023 - Proceedings, 2023, pp. 47-50. DOI: <https://doi.org/10.1109/ICEST58410.2023.10187269>.
- [46] Rudin, C., and Radin, J., When are we using black box models in AI when we don't need to? A lesson from an explainable AI competition, *Harv. Data Sci. Rev.*, 1.2, p. 9, 2019. DOI: <https://doi.org/10.1162/99608f92.5a8a3a3d>.
- [47] Salkin, H.M., and De Kluender, C.A., The knapsack problem: a survey, *Nav. Res. Logist. Q.*, 22(1), pp. 127-144, 1975. DOI: <https://doi.org/10.1002/nav.3800220110>.
- [48] Bisong, E., Google Colaboratory, in Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners, E. Bisong, Ed., Berkeley, CA: Apress, 2019, pp. 59-64. DOI: https://doi.org/10.1007/978-1-4842-4470-8_7.

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