Augmenting Industrial Chatbots in Energy Systems using ChatGPT Generative AI

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2023 IEEE 32nd International Symposium on Industrial Electronics (ISIE) | 979-8-3503-9971-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISIE51358.2023.10228101

***Abstract*—Chatbots, the automation of communicative labor, have been widely deployed in industrial applications and systems. Built upon the Generative Pre-trained Transformer 3 (GPT-3), ChatGPT is a Generative Artificial Intelligence (AI) primed to transform all pre-existing chatbot capabilities with human-like conversation skills. It has already disrupted many disciplines including tertiary education and academic research methods, with increasing adoption in simple to complex tasks. However, the augmentation of pre-existing industrial chatbots with generative AI capabilities has not been fully investigated and demonstrated in recent literature. In this paper, we address this gap by presenting the augmentation of a pre-existing chatbot using ChatGPT generative AI capabilities. Our contribution encompasses the ten primary human-like conversation capabilities of ChatGPT, its augmentation of the pre-existing functionalities and the adopted prompt engineering strategies. Each capability is empirically demonstrated on Cooee, a functionally deployed chatbot in the microgrid energy systems of the La Trobe Energy Analytics Platform (LEAP).**

***Index Terms*—Generative AI, ChatGPT, Chatbots, Energy AI, conversational experience, prompt engineering, Net zero carbon emissions, microgrid optimization, machine learning**

I. Introduction

Chatbots are widely used in many disciplines and industrial domains for the automation of communicative labor, through text or voice and one or more human languages [1]. Many chatbots have been reported in recent research literature, such as mental health chatbot with cognitive skills for personalised behavioural activation [2], [3], chatbots for real-time monitoring and co-facilitation of patient-centered healthcare [4], emotion awareness in industrial chatbots [5]. Most chatbots are designed using predefined routines for information provision or designed to execute repetitive or sequential tasks via conversational inputs [6] and some Artificial Intelligence (AI) capabilities such as prediction, intent classification and user profiling. For instance, in our recent work on Cooee [7], we introduced an AI chatbot that leverages state-of-art language models along with rule-based language processing methods for conversational engagement with dynamic data spaces of energy systems. Energy systems consist of advanced data collection and processing strategies that have enabled a wide range of capabilities in managing, predicting and analyzing heterogeneous streams of energy data [8], [9]. Despite these advances, multi-modalities of data and diverse AI use cases have enhanced the complexity and dynamic nature of these data spaces. Cooee addresses the challenges of such dynamic data spaces in energy systems by taking natural language inputs and converting them to structured statements to access the dynamic data space and respond with natural language with interpretations. This highlights the capability of Cooee to generate responses to user queries on the fly, which is in contrast to pre-defined question-answering (Q&A) chatbots. However, in Cooee the accuracy of responses is highly dependent on the completeness and explicitness of user queries which poses a challenge in achieving more naturalistic conversation.

Human-like conversational AI has many challenges. This is because natural language is a complex and nuanced form of communication that is unique to humans. Creating a chatbot that can understand and respond to natural language in a human-like manner requires a deep understanding of human language and communication, as well as the ability to infer meaning from context [10]. When humans engage in natural language communication, they often make several assumptions about the receiver's level of understanding [11], [12]. With these assumptions, they omit some trivial details and let the receiver fill these gaps on their own using the context. This allows for more efficient communication, as it reduces the amount of redundant information that needs to be conveyed. In the case of chatbots, such contextualized questions can create challenges as they may not have the same level of background knowledge or understanding of the context. Ambiguity, incompleteness, and co-reference resolution are such challenges that can make it difficult for a model to accurately understand and respond to a given text [13], [14].

In more recent developments of generative AI, Generative Pretrained Transformer 3 (GPT-3) was trained on 570 GB of data and 175 billion parameters, and it has outperformed state-of-the-art pre-trained language model (PLM) benchmarks for universal language representation [15]. More recently, GPT-3 was finetuned using Reinforcement Learning with Human Feedback (RLHF) to build Chat Generative Pretrained Transformer (ChatGPT), the world's first PLM with human-like conversational capabilities [16]. Simultaneously, there is an increasing need for prompt engineering [17], [18] which focuses on maximizing outputs of language models considering strengths and weaknesses. For instance, leading organizations such as Snap [19], Instacart [20] and Quizlet [21] have incorporated ChatGPT into their platforms to enhance their services significantly. The ChatGPT model shares a common architecture with its sibling model, InstructGPT [22]. In Instruct-

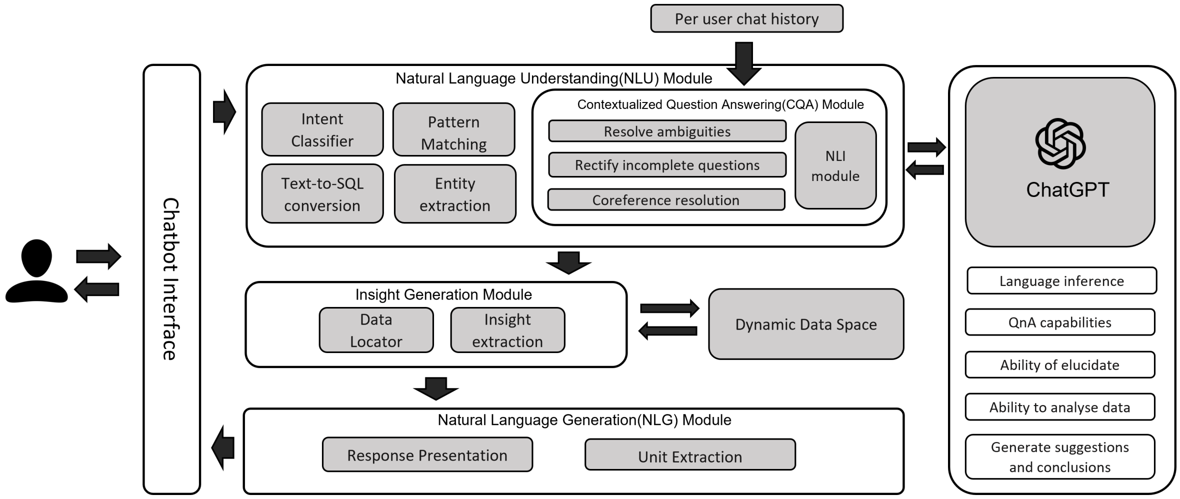

Fig. 1. Architecture for augmenting pre-existing chatbots with ChatGPT

GPT, its functionalities are distributed into ten distinct use cases, namely generation, open and closed question-answering, brainstorming, chat, rewriting, summarization, classification, and extraction. Based on the assumption that ChatGPT inherits these capabilities while also providing a seamless conversational user experience, these use cases can be used to develop energy chatbots with improved conversational abilities.

In this paper, we aim to augment pre-existing chatbots in energy systems by integrating with the ten primary human-like conversation capabilities of ChatGPT [18]. As the primary contribution, we explore how we can use ChatGPT to answer contextualized questions for the three main use cases of resolving ambiguities, rectifying incomplete questions and co-reference resolution for more naturalistic conversation. In order to achieve that we leveraged the natural language inference capabilities of ChatGPT along with heuristics specific to energy systems. Other than natural language inference we also discuss how we can integrate skills such as question answering, the ability to elucidate, the ability to analyse data, and the ability to extract data and generate suggestions and conclusions. The rest of this paper is organized as follows. Section II describes the integration architecture for augmenting pre-existing chatbots with ChatGPT. Section II also presents the implementation of contextual question-answering functionalities and integration of other capabilities of ChatGPT. Section III presents experiments and results from the deployment of Cooee in the Latrobe Energy Analytics Platform (LEAP) deployed at La Trobe University's multi-campus tertiary education setting, and Section IV concludes the paper.

II. Augmentation Architecture for ChatGPT Generative AI

The augmentation architecture for ChatGPT Generative AI is depicted in Fig.1. The general flow of the chatbot consists of the Natural language Understanding(NLU) module, Insight Generation Module and Natural Language Generation(NLG) Module. First, it extracts entities and patterns from the NLU module and constructs corresponding SQL statements, then use these structured statements to extract answers from dynamic data space and finally builds natural language responses with interpretations from the NLG module. For the integration with ChatGPT, we have introduced a new interface through its official API with the model gpt-3.5-turbo [23] in Python programming language. Among the proposed enhancements, contextual question answering requires capturing and resolving user queries within the NLU component, while the others involve direct communication with the ChatGPT interface. Thus, in order to facilitate that we extended the NLU module with contextualized Question Answering(CQA) component. Under the contextualized question answering we are focusing on three main use cases, answer incomplete questions, resolve ambiguities and co-reference resolution.

A. Identify queries which require resolving the context

Under all three use cases of contextualized question answering, initially, the queries will be passed to the NLU module for entity recognition and pattern identification. In order to provide accurate energy information it requires three dimensions which are energy attribute(ATR), the entity or building which is referred to(BLD) and temporal value expressing a datetime or a period(TT). The input queries with all these dimensions can be independently answered by the Cooee. In other cases, these dimensions can be vague or incomplete and need context to resolve. Thus after the entity recognition and pattern-matching tasks, such queries will be identified and forwarded to the CQA module.

B. Utilizing ChatGPT for Contextual question answering(CQA)

The contextual question answering(CQA) module will use chat history as an additional input to acquire the context. In order to facilitate this, per-user chat history will be recorded and stored in a database. In addition to that it will have a

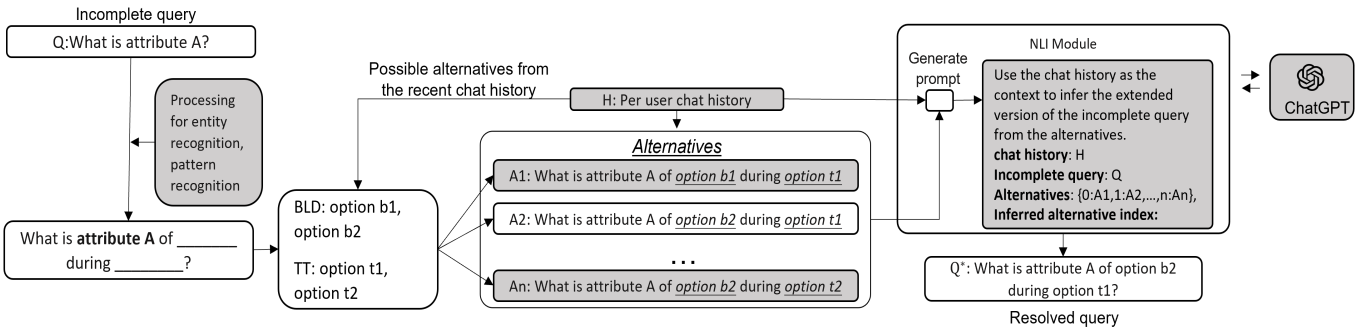

Fig. 2. Responding to incomplete and vague questions

Natural language inference(NLI) module which will communicate with ChatGPT to resolve questions that require contextual knowledge. Here firstly it will identify the missing or co-referring entities and extract suitable options from the recent chat history for them. Afterwards, these options will be used to construct complete alternative versions of the incomplete query.

C. Prompt engineering

Constructed alternatives along with the chat history will be used in the NLI module to populate an input prompt that can be forwarded to the ChatGPT. Here the prompt contains a template to be filled in with chat history, incomplete query and alternative choices. Furthermore, the prompt consisted of an output indicator to facilitate concise response generation. To ensure the deterministic behaviour of the model, the temperature parameter is set to a lower value such as 0.2.

ChatGPT will select the best complete version of the query from the given options and emit the index of it back to the NLU module. This will be chosen as the rectified version of the input query and proceed to the Insight generation and NLG modules for answer extraction. A more elaborated flow diagram of how Cooee resolves vague and incomplete questions is provided in Fig.2.

D. Integrating other skills of ChatGPT

In Addition to the contextualized question answering, The present study expands the Cooee by integrating several additional capabilities of ChatGPT. These functionalities were developed by utilizing the aforementioned use cases and adapting them to suit the energy domain. A detailed description of the extended capabilities and their corresponding use cases are presented in Table I. When constructing the prompts, prefixes such as *"Pretend you are a supportive energy assistant.."* were used to improve and set the temperature to a lower value(0.2) as we primarily used it to extract factual results. These extensions will be further explained in the experiments section with the integration into Latrobe Energy Analytics Platform (LEAP).

TABLE I
AUGMENTING PRE-EXISTING CHATBOT CAPABILITIES WITH CHATGPT

Integrated skill in chatbot	**ChatGPT use-cases**
Natural language inference for answering contextual questions	Closed QA / Rewriting / Classification / Chat
Answering in and out of training-scope energy questions	Open QA / Extraction
Ability to elucidate Energy related concepts, attributes and procedures	Generation / Brainstorming / OpenQA
Ability to analyse tabular data	Generation / Brainstorming / Extraction
Extract data from unstructured sources	Extraction / Classification
Generate suggestions and conclusions	Generation / Brainstorming

III. EXPERIMENTS

A. Contextualized Question Answering experiments

This section explains three use cases of contextualized question answering with Cooee to resolve ambiguities, rectify incomplete questions, and co-reference resolution.

1) Resolve ambiguities: Retrieval of energy information of different entities in the LEAP environment can be ambiguous at times. For an instance, when Cooee is functioning in multi-campus circumstances, asking the question *"What is the energy consumption of the library today?"* can be vague as it does not clearly say which campus library that is referred to. Such situations are typical in human communication and should be resolved to provide more accurate results to the user.

During the chat, once the user has referred to a specific campus name, we cannot expect the user to include the campus name in every subsequent query. Additionally, in such cases, all dimensional data is available in the query "energy consumption"(ATR), "library"(BLD) and "today"(TT) which we can consider as a complete question. So here we use prior chat history to resolve the ambiguous dimension. As the first step, this ambiguous entity will be mapped to n number of disambiguated dimensions such as "library(campus A), library(campus B), library(campus C)" extracted from the chat history. Then ambiguous dimension will be replaced with

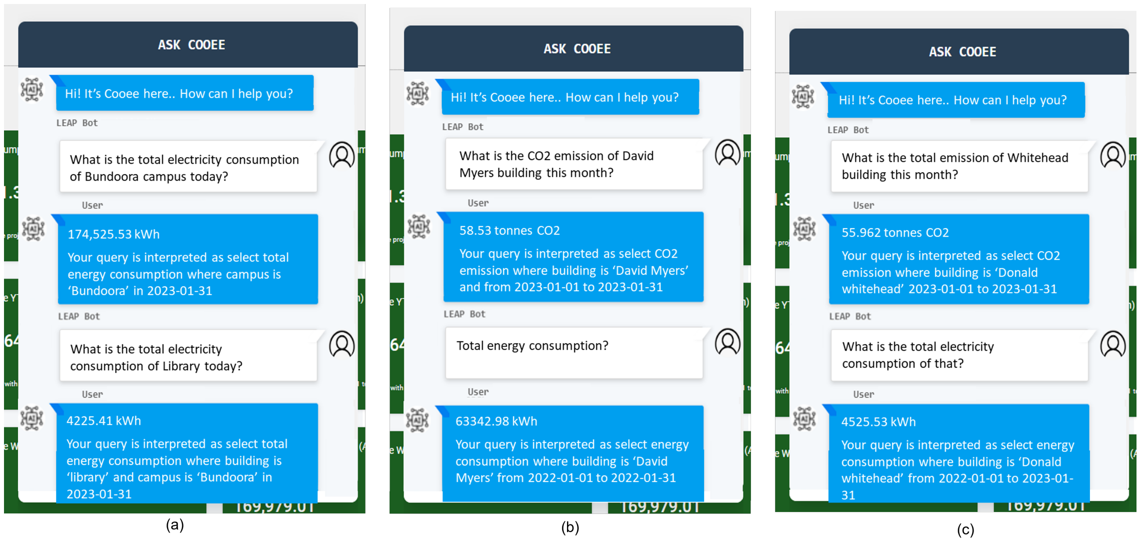

Fig. 3. Contextualized question answering. (a) resolve ambiguous queries, (b) rectify incomplete questions, and (c) co-reference resolution

the options to construct n different disambiguated alternative queries. Then each of these resulting queries along with the user's chat history will be forwarded to the NLI module to construct a prompt and get the query with the highest entailment probability via ChatGPT.

An example is shown in Fig. 3(a), here first user queries about the "Bundoora campus" which is one of the campuses in the LEAP environment. The subsequent query asked about the electricity consumption of the library which is an ambiguous entity. During the contextualization that is resolved and mapped to the library of Bundoora campus to provide accurate answers.

2) Rectify incomplete questions: In human-to-human communication, some information is often intentionally omitted to make the conversation more simple. Since humans can infer such missing information by considering the context, comprehension can be achieved effortlessly even in the presence of incomplete information. But in conversational AI when each user query is treated as a discrete input, deducing omitted information posits a significant challenge. For an instance, the user first queries *"What is the attribute A1 of building B1 today?"* and gets the answers and then poses a follow-up question asking *"What is attribute A2?"*, it can be confusing to the chatbot, as the follow-up question does not contain all information to process the query.

Here the second query contains only an attribute value but does not contain building or date-time information. In such cases, similar to resolving ambiguities, user chat history is used along with natural language inference to infer missing entities to build a complete user query. Here possible options for each of the entities will be taken from the chat history. In case of two missing entities and n1 and n2 possibilities for each of those, n1 x n2 complete alternatives will be considered and the one with the highest entailment probability will be chosen with the ChatGPT following the same pattern as explained in the Fig. 2 and forwarded to text-to-SQL module for further processing.

Fig. 3(b) depicts a scenario of answering an incomplete question. As the first question user queries about CO2 emissions of the David Myers building during this month and gets answers. The subsequent question is posed about energy consumption without explicitly specifying a building or a time frame. Thus, in this case, those dimensions are resolved by considering the chat history.

3) Co-reference resolution: In human dialogues, it's a common feature to employ co-referential expressions. These expressions often take the form of pronouns and are utilized to refer to entities that have been previously mentioned in the conversation. In such cases identifying such pronouns and mapping them to corresponding entities is an important task. To achieve this we extended the entity extraction module to facilitate pronoun detection and map them to correct entities with the help of regex patterns. Then similar to previous use cases these entities will be replaced with the most probable entailment entities considering the chat history.

An example of co-reference resolution is shown in fig. 3(c). Same as previous cases here first it queries about emissions of Whitehead building this month and gets the results. Afterwards, it queries electricity consumption with the co-referring entity "that". Here subsequent query is matching the pattern of "What is [ATR] of [BLD]? and the pronoun is in the place of BLD. Thus, it will be replaced with possible options from the chat context as in the previous cases and the corresponding building name with the highest probability will be chosen.

B. Further augmentations with ChatGPT

1) Answering in and out of training-scope energy questions: This augmentation can be done in two ways. Firstly, by leveraging its own training data to get answers to general questions related to the field of energy. InstructGPT refers to this approach as Open QA in their use case categorization. Some examples of this would be queries such as *"What is renewable energy?"*, *"How does solar energy work?"* The training data utilized for ChatGPT is adequate to deliver highly accurate responses to such queries. Secondly, it is possible to educate ChatGPT to respond to queries that fall outside the scope of its training data but are relevant to the context of the energy chatbot in which it is employed. This can be achieved by providing this information through the prompt itself in the initialization. In the LEAP environment, examples of such questions can be *"What is LEAP?"*, *"What are the goals of the Net Zero Emissions project?"*. Especially in such cases even though the same question is asked in various different forms, ChatGPT exhibits the capacity to accurately associate it with the correct information provided to it. This capability is elaborated as extraction in InstructGPT implementation. These extensions in the chatbot help to preserve the conversational user experience and answer a wide range of user queries.

2) Elucidate conceptual knowledge of energy systems: ChatGPT has the capability to explain concepts and procedures in a clear and concise manner on a wide range of topics. Additionally, it has the special skill of adapting the explanations in different ways, depending on the nature of the information and the level of detail requested by the user. This helps it to adjust the language to meet the expectations of both technical and non-technical audiences. This is explained in use-cases generation, brainstorming and OpenQA. This capability of ChatGPT can be integrated with Cooee to provide clarifications on the concepts associated with energy. An example would be *"Explain how energy forecasting model works to a 5th grader"* or *"Explain the impact of government policies on the field energy"* Furthermore, it can be leveraged to provide a clear and simplified breakdown of advanced procedures which users may find difficult to comprehend such as *"Explain how solar generation works in a step-wise manner*.

Building	Energy consumption today(kWh)	Average energy consumption daily(kWh)
Donald Whitehead Building	1,988	2001.32

Interpretation: *The energy consumption of the Donald Whitehead Building today was 1,988 kWh, which is approximately 99.4% of its average daily energy consumption of 2001.32 kWh. This deviation could indicate a slight reduction in energy consumption compared to the average.*

Fig. 4. Analysis of tabular data

3) Analysis of tabular data: ChatGPT can provide insights, interpretations, and explanations based on patterns, trends, and relationships within tabular data. This feature can be utilized to analyse the output results from the Cooee QnA dashboard. For instance, when Cooee generates the following tabular output, ChatGPT can be used to analyse and build interpretations as depicted in Fig. 4.

Furthermore, we can mention different statistics such as maximum, minimum, and average and ask chatGPT to explain the data using those. Also from the other dashboards where tabular data is presented, can have an additional feature to provide natural language interpretations of those structured data. This ability of ChatGPT can be assumed as a combination of its use-cases generation, brainstorming and extraction.

Input Prompt:
"The university library is constantly working towards reducing its carbon footprint and promoting sustainability. This month, the total energy consumption of the library was measured to be 10,000 kilowatt-hours. The library has also installed solar panels, which generated an impressive 5,000 kilowatt-hours of energy. This has reduced the library's total CO2 emissions by a significant amount. The library building itself is a modern and spacious structure, with five floors and a floor area of 20,000 square feet. The library's efficient design and use of renewable energy sources make it an environmentally friendly addition to the university campus."

put this information into JSON structure {building attribute: xx, value: xx}

Output:
[{ "building attribute": "number of floors", "value": 5 }, { "building attribute": "floor area", "value": 20000 }, { "building attribute": "total energy consumption this month", "value": 10000 }, { "building attribute": "solar generation", "value": 5000 }, { "building attribute": "total emissions (CO2)", "value": "N/A (reduced by solar generation)" }]

Fig. 5. Information extraction.

Input Prompt:
University library shows comparatively higher electricity consumption throughout the year. What are the suggestions to lower consumption?

Output:
Here are some suggestions to lower the electricity consumption of a university library:

1.Install energy-efficient lighting, such as LED lights, which use less energy and last longer than traditional lights.
2.Implement an automatic lighting control system to ensure lights are turned off in unoccupied areas.
3.Encourage natural lighting by keeping windows and curtains open during the day and installing skylights or clerestory windows to increase natural light.
4.Optimize heating, ventilation, and air conditioning (HVAC) systems by regularly servicing and upgrading them, and use programmable thermostats to control the temperature.
5.Invest in renewable energy sources, such as solar panels or wind turbines, to offset the library's energy consumption.

Fig. 6. Generating suggestions and conclusions.

4) Extract data from unstructured sources: Techniques for information extraction from unstructured data have traditionally relied on regular expressions(regexes) which are designed to identify and extract specific patterns within the data. However, the ability to capture different variations of the information segments is hindered by strict patterns. In contrast, ChatGPT has the potential to extract desired information without being restricted to predetermined patterns by leveraging language structures. This capability is primarily depending on the use-case of extraction and it's supported by the classification which distinguishes between different types of information and selects the most appropriate one. Fig. 5.

shows an example of information extraction from unstructured text. In this case, the prompt has been designed with the aim of extracting building attributes and their corresponding values.

5) Generate suggestions and conclusions: ChatGPT has been trained on large amounts of language data which enables it to recognize the associations between words and ideas even in complex and multi-sentence contexts. Furthermore, it can integrate and map these ideas into a coherent central concept which is supported by use-cases generation and brainstorming. This can be utilized to generate suggestions and conclusions from ChatGPT by providing observations and results in the energy domain. Fig. 6. shows an example scenario of deducing some conclusions from ChatGPT.

IV. Conclusion

Genertaive AI models such as ChatGPT are demonstrating advanced human-like conversational capabilities. In this paper, we propose a new architecture for the augmentation of pre-existing chatbot using ChatGPT generative AI capabilities. We report on the ten human-like conversational capabilities of ChatGPT, augmentation of pre-existing functionalities and prompt engineering strategies. Each capability is empirically demonstrated on Cooee, a chatbot deployed in the microgrid energy systems of the La Trobe Energy Analytics Platform. We also demonstrate the primary weakness of ChatGPT generative AI capabilities in that it does not have the epistemological knowledge of a human expert, which can lead to hallucinations and incorrect responses. Thereby, we emphasise the need for effective prompt engineering strategies and domain-relevant heuristics to ensure its accurate and relevant use.

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