OPTIMIZING PROMPTS THROUGH AI FRAMEWORKS: A PATH TO MORE RELEVANT RESPONSES

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ABSTRACT

The rapid growth of large language models has increased the importance of prompt engineering in facilitating effective human-computer interaction. While various frameworks have been developed to assist users with prompt engineering, a comparative analysis of these frameworks and their core components is still lacking. This study addresses this gap by analyzing key terms in widely used frameworks such as RACEF (Role, Audience, Context, Example, Format) to identify recurring elements that are critical to prompt optimization. The findings will lead to actionable recommendations and the development of a unified framework incorporating the most important elements for effective prompt engineering.

Keywords: artificial intelligence, prompt engineering, frameworks, core components

JEL Code: O33, J24

1 INTRODUCTION

The rapid development of large language models (LLMs) has changed the way users interact with artificial intelligence (AI) systems. The quality and relevance of the output from generative AI models largely depend on the quality of the prompts provided. LLMs can achieve significantly improved performance through instruction-tuning, which enables them to precisely follow natural language instructions, allowing them to attain state-of-the-art results in numerous language understanding tasks (Ouyang *et al.*, 2022).

Effective prompt engineering has become an essential tool for ensuring that LLMs generate relevant, accurate, and contextually appropriate responses. To address this need, a range of guidelines, strategies, and frameworks has been developed (Cheng *et al.*, 2023; Korzynski *et al.*, 2023; Schulhoff *et al.*, 2024).

Frameworks for prompting are helpful, but each offers a different set of core components for prompt optimization. Despite the growing number of frameworks available, existing literature and studies have focused primarily on individual frameworks without offering a comparative

https://doi.org/10.11118/978-80-7701-047-4-0029

analysis of their core components. Consequently, it remains unclear which components and strategies are most commonly employed in generating high-quality responses. This study aims to fill this gap by conducting a comparative analysis of key elements used across various frameworks by:

- Identifying core components across existing prompting frameworks.
- Determining which components are most critical for effective prompt design.
- Developing a unified framework that synthesizes established best practices.

This study is guided by two main research questions:

1. What core components are most frequently mentioned across different AI prompting frameworks?
2. What are the gaps and overlaps in existing prompt frameworks, and how might a unified framework contribute to improved prompt optimization?

A preliminary review of existing frameworks indicates significant overlap in terms such as role, context, example, or format. These terms appear consistently across frameworks, indicating their fundamental role in effective prompt design. However, additional terms such as goal, audience, and intent are used less consistently, suggesting potential gaps that warrant further investigation.

Based on preliminary analysis, terms related to role specification, context definition, and example provision are expected to be among the most frequently referenced components across frameworks. Terms such as goal and audience may emerge as secondary considerations, yet remain important. By analyzing the most frequently used core components in popular frameworks, this research will contribute to the advancement of prompt engineering as an emerging field.

2 LITERATURE REVIEW

2.1 Prompt engineering

In generative AI models, a prompt refers to the textual input provided by users that directs how the model should respond. Prompts typically include instructions, questions, input data, or examples. In practice, to elicit a desired response from an AI model, a prompt must contain either instructions or questions, while other elements are optional (Amatriain, 2024). The prompt serves as a form of guidance, helping the model understand what type of output is expected. Prompts can vary greatly in complexity, ranging from straightforward questions to elaborate instructions or detailed task descriptions. By carefully crafting a prompt, users can significantly enhance the relevance and quality of the model's output, making prompt engineering a crucial element in effective AI interaction (Bang *et al.*, 2023).

Prompt engineering in generative AI models is a rapidly evolving field concerned with designing and optimizing prompts to influence the behavior and outputs of these models. Prompt engineering transcends mere prompt construction; it requires a blend of domain knowledge, understanding of the AI model, and a methodical approach to tailoring prompts for diverse contexts (Amatriain, 2024).

Few-shot prompting involves fine-tuning an AI model using a small number of examples that illustrate the desired task. These examples are presented as prompts, allowing the model to understand the task's structure. By analyzing these limited examples, the model learns patterns and generalizes them to handle new inputs, leveraging its pre-trained knowledge to perform the task with minimal examples (Reynolds and McDonell, 2021).

Chain-of-thought prompting structures the interaction to guide the AI model through a coherent, multi-turn conversation by building on the context of previous interactions. The key feature of this approach is its emphasis on maintaining context and coherence across multiple turns, enabling more natural and engaging conversations between the user and the AI model (Wei *et al.*, 2022).

Multi-turn prompting involves users providing an initial input prompt and then refining or adjusting it across several interactions with the AI model. This iterative process allows users to progressively guide the model toward more accurate or relevant responses by clarifying instructions or introducing new information at each step, leading to progressively more relevant and high-quality outputs (Bang *et al.*, 2023).

Each of these methods relies on human experts who possess both task-specific knowledge and a deep understanding of prompting techniques, which restricts their scalability and limits broader applicability (Zamfirescu-Pereira *et al.*, 2023).

While prompt engineering employs these techniques to improve model performance, their complexity highlights the need for more structured approaches. To streamline and standardize the development of effective prompts, specialized AI frameworks have emerged as valuable tools. These frameworks provide a systematic way to design and optimize prompts, enabling more consistent and reproducible outcomes across various tasks.

2.2 Frameworks for prompting

Many frameworks exist across the sciences, but it is not always clear how they are developed and applied (Partelow, 2023). Frameworks for prompting with AI serve as a kind of instruction manual that helps users achieve more effective interactions with artificial intelligence. Prompting refers to the process of guiding the AI toward a desired output, and frameworks help streamline this process so that the AI's responses are more accurate and useful. Without a structured framework, interacting with AI may result in inconsistent or unpredictable responses, making the process feel trial-and-error-based. By contrast, a framework functions as a conceptual template or set of guidelines that organizes prompts into a clear structure, facilitating more accurate interpretation of user requests by the AI model. Frameworks contribute to more effective AI interaction in the following ways:

- Clarifying user intent – improving the AI model's ability to interpret the query accurately.
- Improving response accuracy – ensuring that the model's replies align more closely with the intended outcome.
- Enhancing consistency – reducing variation in responses and making outputs more predictable across repeated prompts.

In summary, frameworks help make AI interactions clearer and more structured, which is particularly valuable for complex tasks that require reliable and accurate answers.

For example, the RACEF framework (Role, Audience, Context, Example, Format) was originally introduced in informal educational and practical AI usage contexts to help non-experts structure prompts more efficiently (Zahid, 2024; Allton, 2024). Similarly, the CARE framework (Context, Action, Result, Example) emphasizes goal-oriented interactions and was developed in UX research for AI-supported tasks (Moran, 2024). However, these frameworks are often evaluated qualitatively or through case-based testing rather than through systematic empirical validation. Some recent studies (e.g., Korzynski *et al.*, 2023; Zamfirescu-Pereira *et al.*, 2023) highlight the need for more formal assessments of framework effectiveness, especially with non-expert users.

2.3 Common prompt components in existing frameworks

Including a **goal** or purpose in an AI prompt ensures clarity and focus, enabling the model to better understand the user's expectations and produce more relevant results (Juuzt, 2025). It reduces ambiguity and guides the AI toward outputs aligned with the intended objectives—whether solving a problem, generating creative content, or analyzing information. A clearly stated goal also helps filter out irrelevant responses, saving users time and effort during refinement. Additionally, it supports prioritization of key aspects within the task, improving the overall quality and precision of the generated output. Overall, including a clearly defined purpose enhances the efficiency and effectiveness of AI interactions.

Assigning a **role** to the AI system helps tailor its responses to a specific context, improving relevance and alignment with the user's needs (Zahid, 2025). When assigned a role—such as teacher, programmer, or consultant—the AI adapts its tone, style, and domain expertise accordingly. This results in more focused interactions that align with the communication context, ensuring that the AI provides solutions, explanations, or advice appropriate to the assigned role. It also enhances the model's ability to simulate real-world scenarios, which supports both problem-solving and creative tasks. Overall, defining a role enhances output accuracy and practical relevance.

AI models rely on clear instructions to generate relevant and accurate outputs (Ozturk, 2025). In 68% of the frameworks analyzed, the **action** component—representing the core task or requirement—is explicitly emphasized to encourage users to formulate clear and specific prompts. A well-defined task description helps guide the AI toward producing focused and appropriate responses, whereas ambiguous or poorly formulated instructions may result in incomplete or irrelevant answers.

Specifying required **steps** in an AI prompt enhances the precision and organization of the model's output by guiding it through a clearly defined process (Juuzt, 2025). By explicitly outlining a sequence of actions or logical steps, the user ensures that the AI approaches the task methodically and that all necessary components are addressed in the intended sequence. This reduces ambiguity and minimizes the risk of incomplete or disorganized responses. It also enables the AI to manage complex tasks more effectively by breaking them into manageable parts, improving both clarity and coherence. Furthermore, step-by-step instructions promote consistency across outputs, making it easier to evaluate results and ensure alignment with the user's expectations.

Including **context** in an AI prompt enhances the relevance and appropriateness of the model's responses by situating them within a specific context or background (Allton, 2024). Context provides the AI with critical information about the audience, purpose, or environment, enabling it to adapt tone, language, and content to the task's specific requirements. This improves the accuracy and usability of the output, particularly in tasks involving nuanced situations such as professional communication or culturally sensitive topics. Additionally, context reduces ambiguity and ensures that the AI fully understands the task environment, leading to more precise, efficient, and targeted results.

Example helps the AI understand the expected format, tone, style, or structure of the response (Moran, 2024). It clarifies the task, reduces ambiguity, and increases the likelihood that the AI will generate output aligned with the user's intentions. This technique is especially valuable in tasks requiring specific patterns, such as writing, coding, or summarization.

When the model produces outputs with consistent errors—such as misinterpreting the prompt or producing formatting mistakes—providing a clear example helps clarify expectations and correct these issues. A concrete example guides the model toward outputs that match the intended tone, content, and structure. This reduces variability in responses and helps maintain overall quality and relevance.

Examples are particularly useful for open-ended tasks or those that could be interpreted in multiple ways. In such cases, an example can explicitly disambiguate the prompt, illustrating the desired direction. In few-shot prompting (Song *et al.*, 2022), examples serve as demonstrations of how to complete the task, offering the model contextual guidance even when the task is unfamiliar or complex.

Moreover, even the order in which examples are provided can influence model behavior. As noted by Lu *et al.* (2022), changing the sequence of examples may lead to different outputs, which gives users an additional strategy for optimizing performance.

Format specifies the desired structure of the AI's response, shaping it to meet the user's specific needs and enhancing clarity, usability, and precision (Saleem, 2024). Defining the output format is essential for ensuring that responses are actionable, consistent with expectations, and practically applicable. This component helps bridge the gap between the model's general capabilities and the user's task-specific requirements, ultimately improving the relevance and effectiveness of AI-generated content.

3 METHODOLOGY AND DATA

The first step involves selecting appropriate frameworks. This step entails compiling a set of widely recognized frameworks commonly used in prompt engineering. Examples include RACEF (Role, Audience, Context, Example, Format), CARE (Context, Action, Result, Example), and RISE (Role, Input, Steps, Execution). These frameworks were selected based on their relevance and established application in diverse AI prompting contexts.

This approach is consistent with methods used in previous studies that involved content extraction and synthesis of framework elements in AI interaction research (e.g., Ozturk, 2025; Zamfirescu-Pereira *et al.*, 2023). The frequency-based analysis enables generalization and reveals the most common semantic components across diverse prompting frameworks.

The next step involves extracting the core components of each selected framework. This includes identifying and categorizing the key terms that characterize the structure and intent of each framework. The extracted terms will serve as the basis for subsequent stages of analysis. Terms with identical or closely related meanings and contexts are grouped for analytical purposes.

Subsequently, a frequency analysis is conducted. In this phase, the occurrence of each core component is calculated across all selected frameworks. This analysis aims to identify the most frequently used terms, thereby highlighting the components essential to effective prompt formulation.

Following the frequency analysis, a comparative analysis is conducted to examine similarities and differences among frameworks. The comparison helps determine which terms are universally applicable and which are specific to individual frameworks.

Finally, based on the results of these analyses, a new unified framework is proposed. This framework incorporates the most critical and commonly used components identified throughout the process. The objective is to develop a refined and comprehensive structure for prompt engineering that addresses existing gaps and enhances the clarity, precision, and effectiveness of AI-generated responses. This methodological approach provides a systematic process for framework development and contributes to the advancement of research in AI prompt engineering.

4 RESULTS

Although a total of 80 distinct terms were identified across all 31analyzed frameworks[1], many of them were semantically similar and served overlapping functions. To enhance analytical clarity, these terms were grouped based on shared meaning and contextual usage. The seven presented components represent the most frequently occurring and semantically dominant categories derived from this grouping process. Less frequent or framework-specific terms were excluded from the final synthesis due to low recurrence or limited general applicability.

1. **Context** (also referred to as ***Audience*** or ***Relevance*** in certain frameworks) is present in 22 out of 31 frameworks (71%). When a user includes context in an AI prompt, they offer background information or situational details to frame the task. This may include specifying the target audience, intended purpose, setting, or other relevant factors that influence how the AI should respond. For example, a user might indicate that the task involves writing for a professional audience, explaining a concept to beginners, or addressing a particular cultural or technical situation. This contextual information helps guide the model toward generating a response that is appropriate and well-suited to the given scenario.
2. **Action** (also referred to as Ask, Task, Requirements, or Request in certain frameworks) occurs in 21 out of 31 frameworks (68%). While task formulation is a fundamental part of every prompt, many frameworks explicitly emphasize this component as central to prompt design. This element typically defines what the user wants the model to do and may also specify input data to be processed as part of the task.
3. **Parameters, Constraints**, or **Format** appear in 18 out of 31 frameworks (58%). This component defines the rules, boundaries, or structural expectations that the AI should follow when generating its response. Typical elements of this component include:
   - **Content constraints** – specifying what the AI should or should not include in its response.
   - **Structural requirements** – defining how the response should be organized.
   - **Length constraints** – setting limits on the length of the output.
   - **Language and style** – indicating tone, formality, or language preferences.
   - **Domain-specific guidelines** – introducing rules tailored to a particular field or audience.
   - **Output format** – determining the exact structure or format of the generated output.
4. **Example** (also referred to as Sample in some frameworks) appears in 14 out of 31 frameworks (45%). Examples provide the AI model with a reference output that illustrates the desired structure, style, or level of detail. By including an example, users can guide the model more effectively toward producing responses that meet specific expectations.
5. **Goal** (also referred to as Expectations, Purpose, or Objective in some frameworks) appears in 14 out of 31 frameworks (45%). Including a clear goal in a prompt helps the AI understand what it is expected to achieve—such as solving a problem, generating content, or analyzing data. Stating a goal reduces ambiguity, improves relevance, and aligns the response with the user's intent.
6. **Role** (also referred to as Character in some frameworks) appears in 13 out of 31 frameworks (42%). Defining a role within the prompt instructs the AI to adopt a particular perspective, profession, or identity when generating responses. For example, the model may be asked to act as a teacher, programmer, salesperson, or consultant, adjusting its tone, vocabulary, and domain knowledge accordingly.
7. **Steps** (also referred to as Instructions or Actions in some frameworks) appear in 11 out of 31 frameworks (35%). This component outlines a specific sequence of operations the AI should follow. It may include breaking down a problem, analyzing individual components, or performing tasks in a defined order to reach a coherent and structured output.

[1]A full list of the frameworks analyzed is available upon request.

Tab. 1 Frequency of Core Components in AI Prompt Frameworks (N=31)

Component	Frequency	Percentage (%)
Context	22	71%
Action	21	68%
Format/Constraints	18	58%
Example	14	45%
Goal	14	45%
Role	13	42%
Steps	11	35%

The framework containing the greatest number of the identified components among the 31 analyzed is the RASCEF framework (Juuzt, 2025). It includes six out of the seven core elements—Role, Action, Steps, Context, Examples, and Format—with the only missing element being Goal. A revised version including Goal could be designated as **GRASCEF**. This extended framework would comprise the following elements: Goal, Role, Action, Steps, Context, Examples, and Format.

To quantify the relevance of individual components, a frequency analysis was conducted. Table 1 presents the number of frameworks (out of 31) that explicitly include each of the seven core components. This analysis confirms that Context and Action are the most commonly used elements, followed closely by Format, Example, and Goal. The results support the validity of the proposed unified framework.

Figure 1 illustrates this distribution graphically, highlighting the dominant components that form the foundation of the GRASCEF framework.

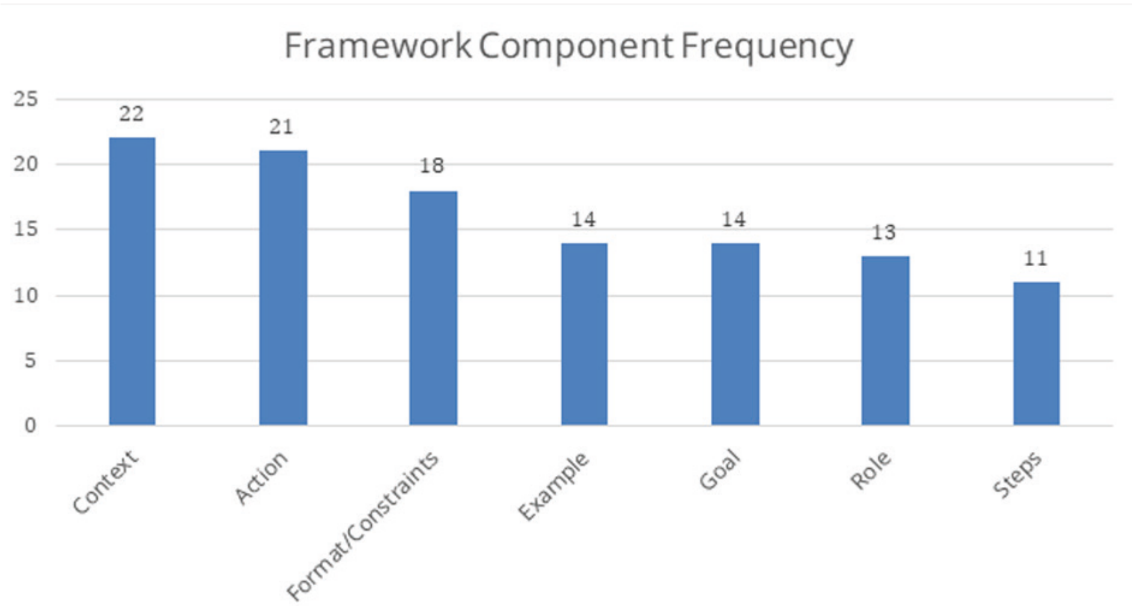

Fig. 1: Distribution of core components in 31 prompting frameworks

5 DISCUSSION

The consolidation of 80 unique terms into seven semantic categories reveals a striking convergence in prompt design practices. Despite originating from diverse contexts, the analyzed frameworks emphasize similar core elements, suggesting that effective prompt engineering may rely on a relatively stable conceptual foundation. The proposed GRASCEF framework represents a synthesis of these shared components and can serve as a practical tool for guiding prompt creation, especially for non-expert users.

An analysis of 31 AI prompting frameworks identified seven semantic prompt components that can enhance the relevance and usability of AI-generated outputs in various ways. By supplementing an existing framework (RASCEF) with the missing component Goal, the GRASCEF framework was formed, incorporating all components identified in the analysis: Goal, Role, Action, Steps, Context, Examples, and Format.

To illustrate the practical application of the GRASCEF framework, the following example shows how each component contributes to a high-quality AI prompt:

- Goal: Generate a professional summary of a research article.
- Role: You are an experienced academic editor.
- Action: Read the article and produce a concise summary focused on methodology and main findings.
- Steps:
    - Identify the research question and hypothesis.
    - Summarize the methods used.
    - Highlight key findings.
    - Note limitations and conclusions.
- Context: The summary will be used by postgraduate students in a research seminar.
- Example: "This study investigates the impact of gamification on user engagement in e-learning platforms. Using a mixed-methods approach with 150 university students, the authors found that leaderboards and badges significantly increased time-on-task and satisfaction. Limitations include short study duration and lack of long-term tracking."
- Format: Bullet-point summary of 150–200 words in academic English.

This example demonstrates how GRASCEF elements guide the AI model toward more structured, accurate, and context-aware outputs. Each component contributes to reducing ambiguity, clarifying expectations, and ensuring relevance—particularly in academic or professional environments.

Furthermore, these recommendations align with previous findings by Zamfirescu-Pereira *et al.* (2023) and Korzynski *et al.* (2023), who emphasize the need for clear, structured prompting guidance especially for non-expert users.

6 CONCLUSION

This study conducted a comparative analysis of 31 existing prompt engineering frameworks and identified seven core components that appeared most frequently. By synthesizing these components into the GRASCEF framework, the study provides a descriptive basis for understanding the common structures behind effective prompt design.

While the findings offer a comprehensive overview of current frameworks and highlight recurring patterns in prompt construction, this research does not yet validate the practical effectiveness of the proposed GRASCEF framework. Therefore, conclusions regarding its impact on prompt quality or user performance should be regarded as preliminary.

The GRASCEF framework may serve as a useful conceptual tool for researchers and practitioners interested in standardizing prompt development. However, its application in practice requires further empirical testing and user evaluation. Future research should focus on assessing the framework's usability, adaptability, and contribution to AI model performance through controlled experiments or case studies in real-world scenarios.

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Acknowledgement

This paper was supported by the project CZ.02.1.01/0.0/0.0/16_017/0002334 Research Infrastructure for Young Scientists, which is co-founded by the Operational Programme Research, Development and Education.

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