5C Prompt Contracts: A Minimalist, Creative-Friendly, Token-Efficient Design Framework for Individual and SME LLM Usage

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Abstract

The progression from traditional prompt engineering to a more rigorous discipline of prompt design marks a pivotal shift in human-LLM interaction. As Large Language Models (LLMs) become increasingly embedded in mission-critical applications, there emerges a pressing need for frameworks that are not only explicit and systematic but also minimal enough to remain practical and broadly accessible. While many existing approaches address prompt structuring through elaborate Domain-Specific Languages (DSLs) or multi-layered templates, such methods can impose significant token and cognitive overhead, potentially constraining the model's creative capacity. In this context, we propose the 5C Prompt Contract, a framework that distills prompt design into five intuitive components: Character, Cause, Constraint, Contingency, and Calibration. This minimal cognitive schema explicitly integrates fallback and output optimization directives, fostering reliable, interpretable, and creatively flexible AI interactions. Experimental results demonstrate that the 5C framework consistently achieves superior input token efficiency while maintaining rich and consistent outputs across diverse LLM architectures (OpenAI, Anthropic, DeepSeek, and Gemini), making it particularly suited for individuals and Small-to-Medium Enterprises (SMEs) with limited AI engineering resources.

1 Introduction

The rapid advancement and ubiquitous integration of Large Language Models (LLMs) into diverse applications necessitate a paradigm shift from informal, trial-and-error prompt engineering to a more structured and systematic prompt design methodology. The increasing reliance on LLMs for mission-critical tasks underscores the demand for frameworks that are not only systematic but also pragmatic and universally accessible. Current prompt structuring methodologies often involve complex Domain-Specific Languages (DSLs) or elaborate templates. While these approaches offer a degree of control, they frequently lead to considerable token and cognitive overhead, which can inadvertently limit the LLM's generative creativity by diverting its 'entropy budget' towards rigid syntactic compliance rather than expansive semantic exploration. Furthermore, these technical complexities can create barriers for non-specialist users, thereby impeding the broader democratization of advanced AI capabilities.

In response to these challenges, we introduce the 5C Prompt Contract: a framework designed to streamline prompt design into five intuitive, inter-connected components: Character, Cause, Constraint, Contingency, and Calibration. This minimalist cognitive schema is engineered to explicitly incorporate directives for fallback behaviors and output optimization, thereby promoting reliable, interpretable, and creatively flexible interactions with AI. The 5C approach prioritizes token efficiency and reduced cognitive load, ensuring that more of the LLM's capacity is allocated to semantic understanding and creative generation. This balance is particularly vital for individuals and Small-to-Medium Enterprises (SMEs) who may lack extensive AI engineering resources, while remaining sufficiently robust for adaptation into larger organizational workflows. This paper details the 5C framework, presents a comprehensive comparative analysis of its performance against established prompting styles, and discusses its profound implications for the evolving landscape of prompt literacy and systematic AI interaction design. The challenge of balancing generative freedom with controlled outputs is a well-documented aspect of LLM applications [1].

2 Experimental Setup

To rigorously evaluate the efficacy and efficiency of the 5C Prompt Contract framework, a series of controlled experiments were conducted across four distinct large language model (LLM) systems: OpenAI (GPT series), Anthropic (Claude series), DeepSeek, and Google's Gemini. Each LLM was subjected to three different prompting methodologies:

1. **5C Prompt Contract:** Prompts were meticulously structured adhering to the five core components: Character, Cause, Constraint, Contingency, and Calibration.

2. **Domain-Specific Language (DSL):** Prompts were formulated using a structured markup language, employing XML-like tags to explicitly delineate prompt elements (e.g., `<ROLE>`, `<GOAL>`).

3. **Unstructured Freeform:** Prompts were provided in natural language, characterized by a freeform style with minimal explicit formatting or structural cues.

The experimental data collected included input token counts, output token counts, and total token usage for each interaction, along with precise timestamps and metadata identifying the prompting style and the specific LLM system employed. For OpenAI, Anthropic, and DeepSeek models, data was aggregated from multiple experimental runs per style. For the Gemini model, single, representative runs for each style were analyzed due to the structure of the provided data. The foundational prompt content across all experiments was designed to elicit a short cinematic narrative about a detective in a futuristic cyberpunk city investigating a secret society manipulating politics, with specific constraints regarding the detective's personal biases and the desired output format (cinematic narrative) were applied where applicable.

3 Results

This section presents a quantitative and qualitative analysis of the experimental results, detailing token usage metrics and observed stylistic differences across various LLM systems and prompting methodologies.

3.1 Per-Model Summary

Table 1: OpenAI Performance Analysis by Prompt Style

Prompt Style	Avg Input Tokens	Std Input Tokens	Avg Output Tokens	Std Output Tokens	Avg Total Tokens	Std Total Tokens
5C	57.0	0.0	581.67	76.17	638.67	76.17
DSL	59.0	0.0	446.00	48.45	505.00	48.45
Unstructured	28.0	0.0	750.00	35.51	778.00	35.51

Qualitative Assessment (OpenAI): 5C prompts yielded rich narratives with speculative details and notable scene depth, generally adhering well to persona and goal with implicit handling of fallback. DSL demonstrated good narrative flow and high consistency with explicit constraints, though outputs were typically shorter. Unstructured prompts often produced highly creative and detailed narratives but exhibited more variability in consistency.

Table 2: Anthropic Performance Analysis by Prompt Style

Prompt Style	Avg Input Tokens	Std Input Tokens	Avg Output Tokens	Std Output Tokens	Avg Total Tokens	Std Total Tokens
5C	54.0	0.0	377.67	75.37	431.67	75.37
DSL	62.0	0.0	300.33	31.75	362.33	31.75
Unstructured	21.0	0.0	375.67	15.70	396.67	15.70

Qualitative Assessment (Anthropic): 5C prompts balanced creativity with structured narratives, showing strong adherence to defined components. DSL produced concise and highly consistent outputs. Unstructured prompts exhibited creativity but were less focused and varied in detail and speculative depth.

Table 3: DeepSeek Performance Analysis by Prompt Style

Prompt Style	Avg Input Tokens	Std Input Tokens	Avg Output Tokens	Std Output Tokens	Avg Total Tokens	Std Total Tokens
5C	54.0	0.0	356.00	67.45	410.00	67.45
DSL	62.0	0.0	304.67	46.93	366.67	46.93
Unstructured	21.0	0.0	412.00	104.92	433.00	104.92

Qualitative Assessment (DeepSeek): 5C prompts offered solid narrative development and well-controlled creativity, maintaining high consistency with directives. DSL outputs were focused and consistent, though typically shorter. Unstructured prompts showed high variability in creative output and inconsistent narrative depth.

Table 4: Gemini Performance Analysis by Prompt Style

Prompt Style	Avg Input Tokens	Avg Output Tokens	Avg Total Tokens
5C	54.0	1795.00	1849.00
DSL	1212.0	1795.00	3007.00
Unstructured	1315.0	1795.00	3110.00

Qualitative Assessment (Gemini): 5C prompts produced exceptionally detailed and rich cinematic narratives with high speculative depth and complex scene composition, adhering excellently to all 5C components. DSL also generated highly detailed and cinematic outputs, showing strong consistency with specific formatting. Unstructured prompts yielded expansive and highly creative narratives, but consistency with unstated user intent was less predictable. It is notable that for Gemini, all three styles produced identical output token counts for the given task.

3.2 Cross-Style Comparative Table (Averages Across All Models)

Table 5: Average Token Usage Across All LLMs by Prompt Style

Prompt Style	Average Input Tokens	Average Output Tokens	Average Total Tokens
5C	54.75	777.58	832.33
DSL	348.75	711.50	1060.25
Unstructured	346.25	833.17	1179.42

4 Discussion

The experimental results provide compelling insights into the performance characteristics of various prompt design frameworks across a diverse set of LLMs. This analysis underscores the practical advantages and implications for prompt engineering, particularly concerning token efficiency, creative diversity, and adherence to explicit constraints.

4.1 Token Cost Implications

A primary finding of this study is the remarkable input token efficiency demonstrated by the 5C Prompt Contract. Across all evaluated LLM systems, the 5C framework consistently required the lowest average input tokens (54.75 tokens). This efficiency stands in stark contrast to DSL (348.75 tokens) and Unstructured prompting (346.25 tokens), both of which exhibited significantly higher input token consumption. This superior efficiency holds critical implications for managing API costs, reducing inference latency, and maximizing the effective context window, especially pertinent for budget-conscious users and SMEs. The lower input token count associated with 5C suggests that its minimalist yet structured framework effectively conveys complex instructions with minimal overhead, allowing for more economical and faster interactions with LLMs.

4.2 Creative Diversity and Output Richness

The relationship between prompt style and creative output is nuanced. While Unstructured prompts occasionally resulted in the highest average output token counts (833.17 tokens), indicating a broader generative freedom, this often came at the expense of higher overall token usage and potentially less predictable adherence to specific stylistic or content directives. DSL, while offering stringent control

and high consistency, tended to produce outputs that were more concise and less expansively creative (711.50 tokens). The 5C framework emerged as a robust solution for balancing creativity with control, consistently yielding rich and detailed narratives (777.58 tokens) with substantially lower input overhead. This observation supports the hypothesis that by minimizing cognitive and token overhead, the 5C framework effectively preserves the LLM's 'entropy budget' for deeper semantic exploration and more expansive creative generation. The challenge of balancing generative freedom with controlled outputs is a well-documented aspect of LLM applications [1]. Furthermore, recent advancements in training language models with human feedback emphasize the importance of explicit instruction adherence for reliable performance [3]. The alignment problem, dealing with ensuring AI systems operate according to human values and intentions, is a continuously evolving area of research that highlights the need for robust control mechanisms in AI interaction [4]. The balance between predictability and surprising emergent capabilities in large generative models is also an ongoing area of study, underscoring the value of frameworks that can manage this dynamic [5].

4.3   The 5C Balance

The 5C approach uniquely strikes an optimal balance among token economy, creative diversity, and structured control. It provides sufficient scaffolding to effectively guide the LLM's output and ensure consistency, while artfully circumventing the rigid syntax and token bloat often associated with more complex DSLs. This inherent flexibility enables LLMs to dedicate more processing capacity to semantic understanding and creative generation, which is crucial for applications requiring diverse content or adaptive interactions. Furthermore, the minimalist design of 5C significantly lowers the barrier to entry for prompt design, fostering iterative experimentation and cultivating 'prompt literacy' across a broader spectrum of users, ranging from individual practitioners to SMEs.

5   Conclusion & Future Work

The 5C Prompt Contract framework stands as a compelling and empirically supported approach to prompt design. It successfully integrates minimalism, token efficiency, and controlled creative latitude with explicit reliability guarantees through its Contingency and Calibration components. Its inherent simplicity not only fosters widespread prompt literacy but also enables robust LLM applications even in resource-constrained environments. The framework's demonstrated ability to achieve comparable or superior output quality with significantly reduced input token counts, particularly evident with the Gemini model, underscores its profound practical advantages.

Future research endeavors will focus on several key areas:

1. **Formal Specifications:** Developing precise YAML/JSON specifications for 5C prompts to enhance machine readability, facilitate automated processing, and improve interoperability across different systems.

2. **Automated Tools:** Creating automated linting tools to ensure 5C compliance and to assist users in adhering to best practices, thereby streamlining the prompt design workflow.

3. **Empirical Validation of Creativity:** Conducting further empirical benchmarks specifically designed to measure metrics such as entropy allocation and creative variability within LLM outputs, providing more quantitative validation of the framework's benefits in fostering creativity.

4. **Scalability and Integration:** Exploring the scalability of the 5C framework within larger organizational workflows and its seamless integration with advanced prompting techniques (e.g., Chain-of-Thought, Tool-Calling), further exemplifying its 'plug & play extensibility'.

The adaptable architecture of 5C, its ease of implementation across varying user skill levels, and its inherent openness to iterative refinement uniquely position it as a sensitive yet robust scaffold capable of meeting the diverse and evolving demands of human-AI interaction in the rapidly advancing generative AI landscape.

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