Prompt Engineering for Structured Data: A Comparative Evaluation of Styles and LLM Performance

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Abstract

Prompt engineering for structured data is an evolving challenge as large language models (LLMs) grow in sophistication. Earlier studies—including our own—tested only a limited set of prompts on a single model, such as GPT-4o [8]. This paper broadens the scope by evaluating six styles—JSON, YAML, CSV, function-calling APIs, simple prefixes, and a hybrid CSV/prefix—across three leading LLMs: ChatGPT-4o, Claude, and Gemini. Using controlled datasets, we benchmark accuracy, token cost, and generation time to deliver the first systematic cross-model comparison of prompt strategies for structured outputs.

Our approach employs structured validation and custom Python utilities to ensure reproducibility, with results visualized through Technique vs. Accuracy, Token Cost, and Time graphs. Our analysis reveals clear trade-offs: simpler formats often reduce cost and runtime with little accuracy loss, while more expressive formats offer flexibility for complex data. These findings underscore how prompt design can be tuned to balance efficiency and versatility in real-world applications.

Our results show prompt choice directly shapes both quality and efficiency. Claude consistently achieves the highest accuracy, ChatGPT-4o excels in speed and token economy, and Gemini provides a balanced middle ground. By extending beyond single-model evaluations, this study offers practical guidance for selecting prompts based on model capabilities and application demands, advancing prompt engineering with a comprehensive, multi-model framework for optimizing structured data generation.

Keywords: Structured Data Generation, LLMs, Prompt Engineering, JSON, YAML, CSV Formats, Token Efficiency Data Validation, Cost-Effective AI.

1 Introduction

Structured data extraction remains a persistent challenge in LLM applications. Modern LLMs show remarkable capabilities in generating structured outputs from unstructured text, offering transformative capabilities in domains like business intelligence, healthcare, and e-commerce [20, 7]. Yet, the quality and efficiency of structured data generation depend heavily on how prompts are designed. Prompt styles vary in structure, verbosity, and interpretability, which significantly influence the output's accuracy, token cost, and generation time [18]. Our earlier study explored these dynamics using GPT-4o and three prompt styles.

This paper builds directly on our prior work [8], which evaluated three prompt styles—JSON, YAML, and Hybrid CSV/Prefix—using GPT-4o alone for structured data generation tasks. In this extended study, we significantly broaden both the prompt design space and the model spectrum, introducing a multi-model comparison framework to generalize and refine earlier insights. Our latest work broadens that investigation across more LLMs and formats to better understand generalizable strategies for prompt-based structured data generation.

While prior studies have explored these differences, there are no comprehensive, cross-model analyses. This paper extends our previous work by examining six prompt styles—JSON, YAML, CSV, function calling APIs, simple prefixes, and a hybrid CSV/prefix format—across three state-of-the-art models: ChatGPT-4o, Claude, and Gemini. This multi-model, multi-format evaluation establishes a comprehensive and generalizable framework for codifying how prompt design affects the accuracy, efficiency, and cost of structured data generation.

Prompting beyond hierarchy: Exploring diverse representations. Hierarchical formats like JSON and YAML are commonly used for their structural rigor and compatibility with downstream systems. However, they can be verbose and computationally expensive, especially when used with large or nested datasets. In contrast, simpler formats, such as CSV and prefix-based prompts, offer more compact representations that are faster and cheaper to process, albeit with potential trade-offs in structure and semantic clarity. Hybrid approaches, such as CSV with prefixed rows,

attempt to bridge this gap by retaining structural cues in a tabular format. Moreover, function-calling APIs, now supported nativelyin many LLMs, provide a formal schema-driven interface that enables strict data validation and integration with programmatic workflows.

Despite the potential of structured data generation [22] with LLMs, limited guidance exists on the optimal prompt styles for achieving high-quality outputs with leading LLMs. Many practitioners prompt via JSON or API function calls due to their structured format and familiarity. Whilte these prompt styles are widely adopted, they may not be optimal in terms of token usage or processing time—especially when dealing with complex and/or large datasets. Alternative prompting techniques, such as simple prefixes, CSV, YAML, or hybrid formats, may offer similar or even better results that consume fewer resources.

Our approach → Evaluating the impact of prompt styles on structured data generation. This paper systematically evaluates six prompting strategies—ranging from hierarchical formats (JSON, YAML) to lightweight representations (CSV, simple prefixes), as well as function calling APIs and hybrid approaches—across three leading LLMs: ChatGPT-4o, Claude, and Gemini. We assess the performance of these six prompting styles across three metrics (accuracy, token cost, and generation time), comparing results across the selected LLMs. Our results quantify the efficiency of each technique and establish practical recommendations for prompt design, particularly where token usage and response time are key considerations.

This paper provides the following contributions to research on optimized prompt techniques for efficient and accurate structured data generation using LLMs:

- We conducted an experiment that generates randomized datasets in three distinct scenarios (personal stories, medical records, and receipts) to evaluate how effectively each prompt style captures the required structure across diverse and context-specific scenarios.
- The datasets we generated for personal stories contain attributes representing individual characteristics and paired them with corresponding valid narratives. Datasets for medical records contain medical attributes to produce valid and realistic entries. Datasets for receipts contain attributes to create valid examples reflecting real-world purchases, following the dataset construction methodology from our previous study [8].
- We used these three datasets to compare the outputs generated by leading LLMs (ChatGPT-4o, Claude, and Gemini) with the expected results. Accuracy was measured based on strict adherence to the original data attributes and values, ensuring the generated structured data matched the intended formats, including JSON, YAML, and CSV.
- We developed an automated validation framework to measure output fidelity, token consumption, and generation latency. These metrics are visualized through comparative graphs—*Technique vs. Accuracy*, *Technique vs. Token Cost*, and *Technique vs. Time*, highlighting the trade-offs across prompt styles and LLMs.

Rationale for prompt formats and real-world use cases. We selected the following six prompt formats to mirror common production pathways for structured data:

- **JSON**—The default interchange for web and microservices, which enables strict nesting and schema validation in downstream ETL/ELT and API contracts.
- **YAML**—Human-editable configuration prevalent in DevOps (*e.g.*, CI/CD pipelines and Kubernetes manifests), offering readability with hierarchical structure.
- **CSV**—Tabular format ubiquitous in analytics, BI pipelines, spreadsheets, and data lake ingestion; lightweight and token-efficient.
- **Function Calling APIs**—Direct alignment with LLM tool/function APIs used in production (*e.g.*, structured outputs validated by JSON Schema) to minimize parsing errors.
- **Simple Prefixes**—Label–value pairs favored in low-latency agents and logging pipelines since it's compact and robust for shallow structures.
- **Hybrid CSV/Prefix**—Combines tabular headers with required placeholders for missing values, reflecting realistic ingestion constraints where all columns must remain present.

These choices capture the practical spectrum from hierarchical rigor (JSON/YAML) to minimal, low-cost encodings (CSV/Prefixes), and a middle ground (Hybrid) that preserves column integrity while controlling verbosity.

Paper organization. The remainder of this paper is organized as follows: Section 2 summarizes the open research questions addressed in our study and outlines our technical approach; Section 3 explains our experiment design, datasets, and testbed environment; Section 4 analyses the results of experiments that evaluate the efficiency, accuracy, and cost-effectiveness of different prompting strategies for structured data generation using LLMs; Section 5 provides a comparative analysis of the performance of ChatGPT-4o, Claude, and Gemini on our datasets; Section 6 compares our research with related work; Section 7 outlines our study's current evaluation scope and highlights future extensions; and Section 8 presents lessons learned from our study and outlines future work.

2 Summary of Research Questions

Four research questions guide our study by evaluating the effectiveness of different prompt styles on structured data generation by leading LLMs. Each question

addressed a specific aspect of prompt performance, focusing on accuracy, efficiency, and cost-effectiveness. These questions build upon the research framework introduced in our earlier study [8], which focused on prompt-style evaluation for structured data generation using GPT-4o. This paper extends those questions across a broader range of prompt styles and evaluate them using multiple state-of-the-art LLMs to gain deeper, more generalizable insights, as described below:

- **Q1: Which prompt style produces the most accurate structured data for each LLM?** We examined how well each style captured attribute completeness and correctness by comparing generated outputs against predefined test datasets. This comparison allowed us to identify which styles most reliably preserved the intended structure and values across models.
- **Q2: What is the token cost of each prompt style, and which delivers the best cost-effectiveness?** Since token usage directly drives API expenses, we measured the consumption of each style to see which minimized costs while still maintaining accuracy—an essential factor for applications where efficiency and scale matter.
- **Q3: How does each prompt style perform in terms of generation speed?** We recorded the time each LLM required to produce structured outputs, highlighting which styles generated results most quickly. This metric is particularly relevant for real-time or high-volume scenarios where response time is critical.
- **Q4: Do some prompt styles perform better for certain data types or scenarios?** To assess context sensitivity, we applied each style to varied datasets (e.g., personal stories, receipts, medical records) to determine whether specific styles offered advantages depending on the structure, complexity, or domain of the data.

3 Experiment Design

To address the research questions in Section 2, we developed a multi-stage study involving randomized data generation, prompt formulation [12], interactions with multiple LLMs [24], and validation of generated outputs. This study evaluated the efficiency, accuracy, and cost-effectiveness of six prompting styles (JSON, YAML, CSV, API function calls, simple prefixes, and a hybrid CSV/prefix format) to generate structured data across three data contexts (personal stories, receipts, and medical records). To ensure a comprehensive analysis, we performed this study using three leading LLMs (ChatGPT-4o, Claude, and Gemini).

This experiment builds upon our earlier study, which evaluated structured data generation using three prompt styles (JSON, YAML, and Hybrid CSV/Prefix) with GPT-4o alone [8]. In this work, we significantly extend the experiment design by introducing three additional prompt styles (CSV, API function calls, and Simple Prefixes) and comparing them across three leading LLMs. We also reuse and expand upon the randomized datasets and evaluation framework from our prior work to maintain consistency while enabling multi-model analysis. Some figures and validation methodologies presented in this section are adapted from the original study with updated results and formatting.

Systematically assessing the performance of each prompt style per LLM identified optimal formats for structured data generation-based token usage, processing time, and accuracy metrics. Our experiment was structured into

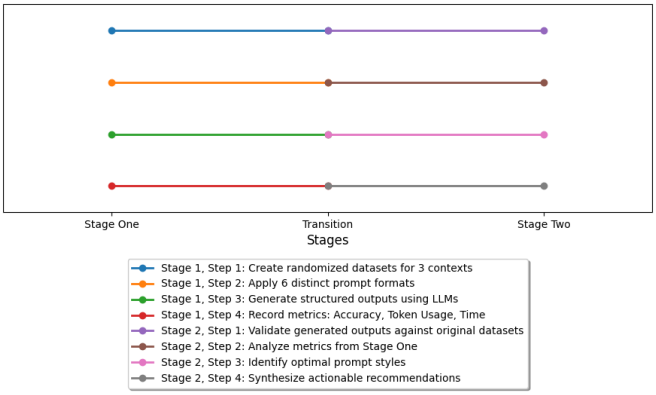

Figure 1. Visualization of Study Stages

two stages shown in Figure 1 and described below, following and expanding the design of our prior GPT-4o-only study [8].

- **Stage One: Data Generation and Prompt Testing**. This first stage created randomized datasets tailored to the three contexts (personal stories, receipts, and medical records) and applied six distinct prompt style (JSON, YAML, CSV, API function calls, Simple Prefixes, and Hybrid CSV/Prefix) to guide the LLMs in generating structured outputs. Three metrics aAccuracy, token usage, and generation time) were recorded for each combination of LLM and prompt style.
- **Stage Two: Assessment and Refinement**. This second stage validated the outputs generated by each LLM against the original datasets to measure accuracy. The metrics collected during Stage One were assessed to identify the most efficient and effective prompt styles. The results were codified into actionable recommendations that highlight the strengths and trade-offs of each prompt style for different data contexts and LLMs.

3.1 Stage One: Data Generation and Prompt Testing

The first stage of our study developed and validated datasets simulating realistic data generation scenarios

across three contexts: personal stories, receipts, and medical records. Each dataset [10] includes diverse attributes (e.g., name, age, city, email) formatted under consistent guidelines to ensure comparability. These datasets form the foundation for Stage Two, where we evaluate the effectiveness of different prompt styles (Section 3.2).

Our dataset generation process began by randomizing attributes to include diversity, such as optional fields like *email*. These attributes were embedded into prompts instructing each LLM to generate a narrative that incorporated all specified details. Each generated story was then validated against the original attributes using pattern-matching to ensure accuracy and completeness.

The validation process ensured every input dictionary attribute was reflected accurately in the generated story. This process extracted relevant paragraphs for each individual attribute using a pattern-matching algorithm and compared each attribute from the input against the generated text to verify inclusion. Any missing attributes were logged for further refinement to ensure generated outputs met the expected requirements of accuracy and completeness.

3.1.1 Personal Stories Dataset and Validation

The *Personal Stories Dataset* tests each LLM's ability to weave structured input attributes into coherent narrative outputs. It simulates use cases where structured data must appear naturally within free-form text while preserving every required attribute. This systematic generation process ensured consistency, accuracy, and validity throughout. To create this dataset, random attributes were generated for fictional individuals, including fields like *name*, *age*, *city*, and optionally *email*, as shown in Figure 2. These attributes

```
{   "people": [ {
      "name": "dkmotp",
      "age": 3
    }, {
      "name": "mlumld",
      "city": "London"
    }, {
      "name": "fanonr",
      "email": "uytgoy@example.com"
    }, {
      "name": "jntsxr",
      "age": 33,
      "city": "New York",
      "email": "xqnmth@example.com"
    } ] }
```

Figure 2. Random People Generation Example (adapted from [8])

were structured in dictionaries where each entry represents a unique individual. The randomization ensured diversity and tested each LLM's capability to handle variations in input attributes effectively.

```
## Problem Statement
- Write a short, single-paragraph story
  about the individuals listed below.
## Constraints
- Ensure that every value in the dictionary
  is included exactly as provided.
- The values must be explicitly stated in
  the story so they can be verified using
  `.contains({people})`.
## Input
- `people`: A list of randomly generated
   dictionaries representing individuals.
```

Figure 3. Prompt Generating Personalized Stories (adapted from [8])

Figure 3 shows the LLM prompt used to generate personalized stories. This prompt was designed to ensure each LLM generated a short, single-paragraph narrative that explicitly included every attribute from the input dictionary. Moreover, this prompt enforced the inclusion of all attribute values exactly as provided, enabling rigorous validation of the generated outputs, as shown in Figure 4.

```
## Story
In a twist of fate that only destiny could
orchestrate, dkmotp, a bright-eyed curious
3-year-old, found himself at a bustling
carnival in the heart of London. Just steps
away, mlumld, who had spent her entire life
in this vibrant city, was mesmerized by the
lively atmosphere, unaware her path was
about to cross with others in strange ways.
As fanonr admired the colorful parade, busy
typing an email to uytgoy example.com, she
accidentally bumped into jntsxr, a 33-year-
old from New York who was in town to escape
the familiar chaos of his life. He quickly
glanced at his phone to ensure nothing had
happened to his email draft addressed to
xqnmth@example.com. Little did they know,
their lives were about interconnect by the
most unexpected series of events.
```

Figure 4. LLM-generated Personalized Stories (adapted from [8])

The validated stories were formatted into six distinct styles for further analysis and experimentation: (1) JSON for hierarchical structures with nested attributes, (2) YAML for human-readable formats, (3) CSV for flat tabular data representation, (4) API function calls for encapsulating structured data, (5) Simple prefixes for lightweight labeled fields, and (6) Hybrid CSV/prefix for combining tabular headers with prefixed rows. Section 3.2 assesses each format for accuracy, efficiency, and token usage in subsequent stages of the experiment, providing a comprehensive understanding of their relative strengths and weaknesses.

3.1.2 Medical Record Dataset

The *Medical Record Dataset* evaluates the ability of each LLM to generate structured medical records that accurately represent input attributes. This dataset simulates real-world scenarios where structured patient data is embedded within electronic medical records, while preserving the completeness and correctness of all specified details. The generation process followed a systematic methodology to ensure consistency, accuracy, and validity.

To create the dataset, random attributes were generated for fictional individuals, including fields such as *name*, and optionally *age*, *city*, and *email*. Likewise, medical-specific fields, such as *diagnosis*, *prescriptions*, and *doctor's notes*, were included but are considered outside the scope of this experiment. These attributes were organized into dictionaries, with each entry representing a unique individual. Figure 2 depicts the random person generation process for the *Medical Record Dataset*.

Randomizing attributes ensured diversity and tested each LLM's ability to handle varying input fields effectively. The prompt shown in Figure 5 guided each LLM to generate structured medical records that include every attribute from the input dictionary. This prompt included all specified at-

```
## Problem Statement
Write a structured medical record for each
individual listed below.
## Constraints
- Ensure that every value in the dictionary
  is included  exactly as provided.
- The values must be explicitly stated in
  the record so they can be verified using
  `.contains({{people}})`.
## Input
- `people`: A list of randomly generated
   dictionaries representing individuals.
## Output Format
Write medical records using this format:
## Patient Information: X
- Name: [Name] (required)
  - Age: [Age] (optional)
  - City: [City] (optional)
  - Email: [Email] (optional)
Ensure the records are formatted as shown
above and all names are listed exactly
as provided in the dictionary.
```

Figure 5. Prompt Generating Medical Records

tributes and ensured the generated medical records followed the required structure and formatting. Figure 6 shows examples of the LLM-generated medical records.

3.1.3 Receipt Dataset

The *Receipt Dataset* evaluates each LLM's ability to generate structured receipts that represent input attributes accurately. This dataset simulates real-world scenarios where

```
## Patient Information: 1
- Name: dkmotp
  - Age: 3
## Patient Information: 2
- Name: mlumld
  - City: London
## Patient Information: 3
- Name: fanonr
  - Email: uytgoy@example.com
## Patient Information: 4
- Name: jntsxr
  - Age: 33
  - City: New York
  - Email: xqnmth@example.com
```

Figure 6. LLM-generated Medical Record

structured information about transactions or individuals is embedded within formal receipt templates, while preserving the completeness and correctness of all specified details. The generation process applied a systematic prompt style to ensure consistency, accuracy, and validity.

To create the dataset, random attributes were generated for fictional individuals, including fields such as *name*, and optionally *age*, *city*, and *email*. These attributes were organized into dictionaries, with each entry representing a unique individual. Figure 2 depicts the random person generation process for the *Receipt Dataset*.

Randomizing attributes ensured diversity and tested each LLM's ability to handle varying input fields effectively. The prompt shown in Figure 7 guided each LLM to generate structured receipts that explicitly included every attribute from the input dictionary. This prompt enforced the inclu-

```
## Problem Statement
- Write a structured receipt for each
  individual listed below.
## Constraints
- Ensure that every value in the dictionary
  is included exactly as provided.
- The values must be explicitly stated in the
  receipt so they can be verified using
  `.contains({{people}})`.
## Input
- `people`: A list of randomly generated
   dictionaries representing individuals.
## Output Format
Write receipts using the following format:
## Receipt for Person: X
  - Name: [Name] (required)
  - Age: [Age] (optional)
  - City: [City] (optional)
  - Email: [Email] (optional)
Ensure all names are listed exactly as shown
in the dictionary and only include optional
fields if they are provided.
```

Figure 7. Prompt Generating Receipt Records

sion of all specified attributes and ensured the generated receipts follow the required structure and formatting. Figure 8 shows examples of LLM-generated receipts.

```
## Receipt for Person 1
- Name: dkmotp
  - Age: 3
## Receipt for Person 2
- Name: mlumld
  - City: London
## Receipt for Person 3
- Name: fanonr
  - Email: uytgoy@example.com
## Receipt for Person 4
- Name: jntsxr
  - Age: 33
  - City: New York
  - Email: xqnmth@example.com
```

Figure 8. LLM-generated Receipt Records

3.2 Stage Two: Assessment and Refinement

The second stage of our study evaluated outputs from three LLMs—ChatGPT-4o, Claude, and Gemini—using the datasets introduced in Section 3.1. Building on Stage One's metrics, we assessed each prompt style for accuracy, efficiency, and token cost, providing actionable insights into their relative performance. As detailed in Section 4, this analysis highlights the strengths, limitations, and trade-offs of all six styles across the *Personal Stories*, *Medical Records*, and *Receipts* datasets.

Stage Two employed six distinct prompt styles—JSON, YAML, CSV, API function calls, Simple Prefixes, and Hybrid CSV/Prefix—each crafted to represent structured data in a specific format. These styles were applied to test how effectively each LLM could generate outputs that were both accurate and efficient, as described below.

The JSON prompt Figure 9 instructs each LLM to create a structured JSON output adhering to a predefined schema. This format is hierarchical and suitable for applications requiring nested structures. The YAML prompt shown in Figure 10 emphasizes human-readability while maintaining strict formatting standards, making it a versatile option for both human and machine interpretation.

```
Create valid JSON output using this schema:
{   "people": [ {
            "name": "<name>",
            "age": <age>,
            "city": "<city>",
            "email": "<email>"
        },
    ... # Repeat for other people in story
    ]
}
If any attributes (name, age, city, email)
are not present for a person in the story,
omit them from that person's JSON object.
```

Figure 9. Prompt in JSON Format

```
Create valid YAML output using this schema:
  people:
    - name: <name>
    - age: <age>
    - city: <city>
    - email: <email>
    # Repeat for other people in story
If any attributes (name, age, city, email)
aren't present for a person in the story,
omit that attribute from that YAML object.

**Ensure the YAML output begins with
'```yaml' and ends with '```'.**
```

Figure 10. Prompt in YAML Format

The CSV prompt shown in Figure 11 represents the data in a flat, tabular format, ensuring simplicity and compatibility with data analysis tools. The API function call prompt in Figure 12 simulates an API interaction by formatting the data as function arguments in JSON, challenging each LLM to meet schema requirements precisely.

```
Create a CSV file based on this schema:
        Name, Age, City, Email

If any attributes (Name, Age, City, Email)
are not present for a person in the story,
leave that field blank in the CSV output.

**Ensure the CSV output begins with
'```csv' and ends with '```'.**
```

Figure 11. Prompt in CSV Format

The Simple Prefix prompt shown in Figure 13 generates structured text using labeled fields (*e.g.*, 'Name:', 'Age:'), focusing on human-readability and lightweight representation. Finally, the Hybrid CSV/Prefix prompt shown in Figure 14 combines elements of tabular data and prefixed text, requiring each LLM to maintain placeholders for all attributes, even when values are absent.

Each of these six prompts was crafted carefully to evaluate how effectively each LLM interpreted and adhered to the provided instructions. The outputs generated from these prompts were then validated against the three *Personal Stories*, *Medical Records*, and *Receipts* databases to measure accuracy. Each dataset was generated using prompts that were identical across ChatGPT-4o, Claude, and Gemini to provide a fair comparison by avoiding any LLM-specific tailoring. This approach ensured our evaluations reflected each LLMs' inherent capabilities without introducing bias from prompt tailoring [6].

We evaluated the performance of these six prompt styles systematically by applying them to the three datasets for all three LLMs. Our assessment identified the strengths

```
Use OpenAI's API to invoke a function named
`answer` with the following schema:
{ "$schema":
  "http://json-schema.org/draft-07/schema#",
  "type": "object",
  "properties": {
     "people": {
        "type": "array",
        "items": {
          "type": "object",
          "properties": {
             "name": {
                "type": "string"
             },
            "age": {
                "type": "string"
             },
             ... # Repeat for city & email
          },
          "required": ["name"]
        } } },
    "required": ["people"]
}
For each person in the story, include their
information as an object within the "people"
array. If any attributes (name, age, city,
email) aren't present for a person in the
story, omit that parameter in their object.

**Ensure the API function call output begins
 with '```json' and ends with '```'.**
```

Figure 12. Prompt in API Function Call Format

and weaknesses of each prompt style by comparing LLM-generated outputs against expected data via the following three measures:

- *Accuracy measures*. which calculated the percentage of attributes correctly included in the generated output,
- *Token usage measures*, which evaluated the number of tokens consumed by each prompt style for each LLM, as token efficiency directly correlates with cost,
- *Time efficiency measures*, which computed response times for generating outputs to assess the suitability of each LLM for real-time or batch processing tasks.

Our schema validation [4] process ensured every attribute from the input datasets was reflected accurately in the generated LLM outputs. As discussed in Section 4 below, the findings from Stage Two codified actionable recommendations when selecting the most effective LLM and prompt style combinations for different structured data generation tasks.

4 Analysis of Experiment Results

This section compares the performance of ChatGPT-4o, Claude, and Gemini's in accordance with the assessment process described in Section 3.2. This analysis builds

```
Create structured text output using prefixes
based on this schema where available:
    Name: <name>
    Age: <age>
    City: <city>
    Email: <email>
If any attributes (Name, Age, City, Email)
are not present for a person in the story,
omit that line in the output.

**Ensure each person's details are
separated in output.**
```

Figure 13. Prompt in Simple Prefix Format

```
Create structured output using a hybrid of
CSV and simple prefixes based on this
schema,:
        row: name, age, city, email
Ensure the first row includes the header and
each column has a placeholder, even if the
value is not present.

For each person in the story, extract their
name, age, city, and email, and format it
as a CSV string prefixed by 'row'. The first
line must always be "row: name, age, city,
email". For subsequent rows, if any of these
attributes are not present for a person,
leave that field empty while keeping the
comma as a placeholder.

**Ensure the Hybrid CSV/Prefix output begins
with '```hybrid' and ends with '```'.**

The output should retain all columns in the
order specified, even if some values are
missing. Use the information extracted from
this story:
{ In a twist of fate that only destiny could
orchestrate, dkmotp, a bright-eyed curious
3-year-old, found himself at a bustling
carnival in the heart of London. Just steps
away, mlumld, who had spent her entire life
in this vibrant city, was mesmerized by the
lively atmosphere, unaware her path was
about to cross with others in strange ways.
As fanonr admired the colorful parade, busy
typing an email to uytgoy example.com, she
accidentally bumped into jntsxr, a 33-year-
old from New York who was in town to escape
the familiar chaos of his life. He quickly
glanced at his phone to ensure nothing had
happened to his email draft addressed to
xqnmth@example.com. Little did they know,
their lives were about interconnect by the
most unexpected series of events.}
```

Figure 14. Prompt in Hybrid CSV Simple Prefix Format

upon our previous GPT-4o-focused evaluation [8], which explored the trade-offs among three prompt styles (JSON, YAML, Hybrid CSV/Prefix) using a single-model setup. In this extended study, we broaden the scope significantly by evaluating six prompt styles across three advanced LLMs. While the datasets and visualization strategies (e.g., prompt style vs. accuracy, token cost, and generation time) retain elements from our prior methodology, all results, graphs, and comparisons have been re-executed with the expanded set of prompt styles and LLMs to ensure comprehensive, model-specific insights.

4.1 Analysis of ChatGPT-4o Experiment Results

We first analyze the results of applying ChatGPT-4o across our three *Patient Information*, *Personal Story*, and *Receipt* datasets for each of the three accuracy, token usage, and time efficiency measures.

4.1.1 Accuracy Analysis for ChatGPT-4o

Figure 15 depicts ChatGPT-4o's accuracy for all six prompt styles and three datasets. The results indicate ChatGPT-

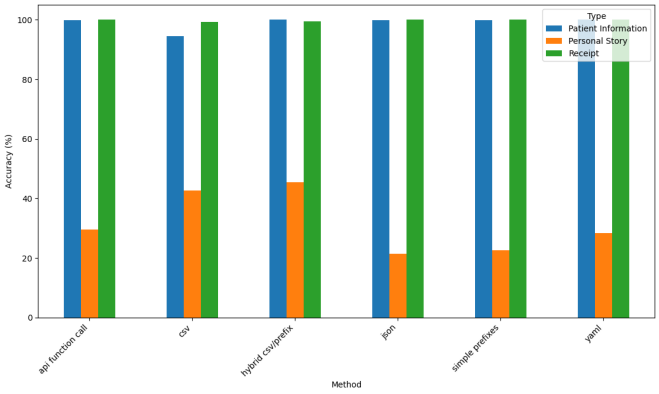

Figure 15. ChatGPT-4o Accuracy by Prompt Style and Type (extended from [8])

4o achieves consistently high accuracy (nearly 100%) for structured datasets (*i.e.*, *Patient Information* and *Receipt*) across all prompt styles. Its performance declines significantly, however, for the narrative-style *Personal Story* dataset, where its accuracy ranges between 20%-40%.

ChatGPT-4o's disparity in performance highlights its challenges when structuring narrative data compared to well-structured formats. The API Function Call, YAML, and Hybrid CSV/Prefix prompt styles exhibit strong performance, particularly for structured datasets. JSON demonstrates variability in accuracy, however, particularly for *Personal Story* data. These results underscore ChatGPT-4o's strengths in handling structured data formats, while revealing its limitations in unstructured and narrative contexts.

4.1.2 Token Usage Analysis for ChatGPT-4o

Figure 16 shows ChatGPT-4o's token usage for all six prompt styles and three datasets. These results show the

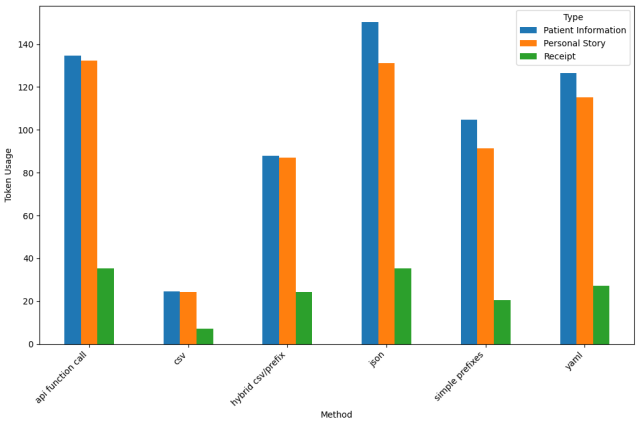

Figure 16. ChatGPT-4o Token Usage by Prompt Style and Type (extended from [8])

API Function Call and JSON prompt styles consume the highest number of tokens, particularly for *Patient Information* and *Personal Story* datasets, which generate verbose and structured outputs that increase token usage.

In contrast, the CSV prompt style exhibits the lowest token usage across all dataset types, demonstrating ChatGPT-4o's efficiency in producing concise tabular outputs. Among the dataset types, the *Receipt* dataset consistently shows lower token usage for all prompt styles. This result reflects the reduced complexity and structured nature of ChatGPT-4o for transactional data.

The Hybrid CSV/Prefix and Simple Prefixes prompt styles balance token usage and maintain moderate verbosity. These results highlight ChatGPT-4o's ability to minimize token consumption while ensuring high-quality outputs for structured and semi-structured datasets. ChatGPT-4o does exhibit notable variability, however, influenced by both prompt style and dataset type.

4.1.3 Time Analysis for ChatGPT-4o

Figure 17 visualizes the processing times of ChatGPT-4o across all the prompt styles and dataset types. These results

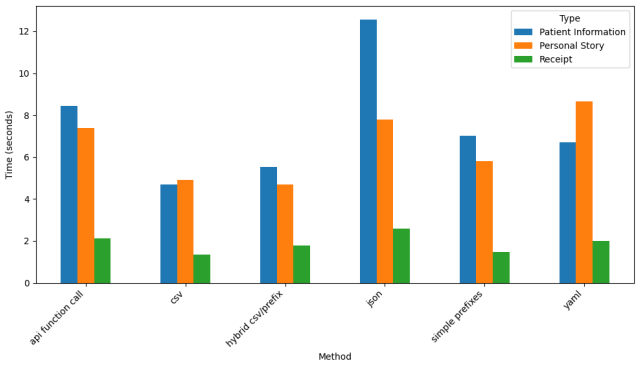

Figure 17. ChatGPT-4o Time Taken by Prompt Style and Type (extended from [8])

indicate that the API Function Call and JSON prompt styles exhibit the highest processing times, particularly for *Patient*

Information and *Personal Story* datasets. JSON processing for *Patient Information* reaches over ten seconds, reflecting the complexity of generating detailed structured outputs.

In contrast, the CSV prompt style and *Receipt* dataset show the lowest processing times across all prompt styles, with times often below three seconds. These results show ChatGPT-4o generates concise outputs efficiently for transactional data in simple formats. The Hybrid CSV/Prefix and YAML prompt styles show moderate processing times across datasets, balancing complexity and output quality.

In general, processing times for *Patient Information* datasets remain consistently higher than for other types, highlighting the intricacy of these structured inputs. These findings underscore ChatGPT-4o's efficiency in simpler formats and transactional data while revealing its challenges in handling complex, hierarchical outputs.

ChatGPT-4o demonstrates a mix of strengths and weaknesses across accuracy, token use, and runtime. It performs well on structured datasets like *Patient Information* and *Receipt*, particularly with YAML and API Function Call prompts, but struggles with the more open-ended *Personal Story* dataset. Its efficiency with compact formats like CSV makes it ideal for token-constrained tasks, though verbose styles such as JSON and API Function Call significantly increase token consumption.

Finally, ChatGPT-4o exhibits competitive time efficiency by processing simpler formats like CSV and *Receipt* datasets quickly. However, more complex prompt styles and datasets, such as *Patient Information* and JSON, demand significantly longer processing times. These results reaffirm and extend our earlier findings on ChatGPT-4o [8], confirming its strength in structured data generation and identifying new trends when evaluated across a broader spectrum of prompt styles and datasets.

4.2 Analysis of Experiment Results for Claude

This section analyses Claude's performance across the three *Personal Stories*, *Medical Records*, and *Receipt Records* datasets described in Section 3.1. Claude was evaluated using customized prompts designed to leverage its strengths in generating structured outputs while adapting to the varying complexities of the datasets. As with ChatGPT-4o, accuracy, token usage, and generation time metrics were analyzed to quality how well the Claude LLM (1) captured the essential attributes of each dataset and (2) how effectively it handled the trade-offs between verbosity, efficiency, and output quality. This analysis provides insights into Claude's ability to handle structured and narrative data, offering a comparative perspective against other LLMs.

4.2.1 Accuracy Analysis for Claude

Figure 18 depicts Claude's accuracy across various prompt styles and dataset types. These results reveal that Claude achieves consistently high accuracy (close to 100%) for

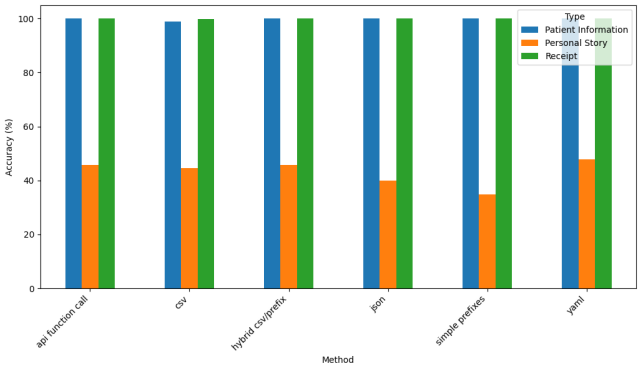

Figure 18. Claude Accuracy by Prompt Style and Type

structured datasets, such as *Patient Information* and *Receipt* across all prompt styles, demonstrating its strength in handling structured data effectively. Its performance drops significantly, however, for the narrative-style *Personal Story* dataset, with accuracy stabilizing at around 40% across all prompt styles.

This analysis highlights Claude's uniform performance across different prompt styles (such as API Function Call, YAML, and CSV), reflecting its robustness in generating output for structured datasets. For less structured datasets, such as *Personal Story*, Claude's accuracy remains consistent regardless of prompt style, indicating that dataset complexity, rather than prompt structure, plays a more significant role in its performance. These findings underscore Claude's reliability in structured tasks, while identifying areas for improving its narrative-style data generation.

4.2.2 Token Usage Analysis for Claude

Figure 19 depicts the token usage of the Claude LLM across various prompt styles and dataset types. These results indi-

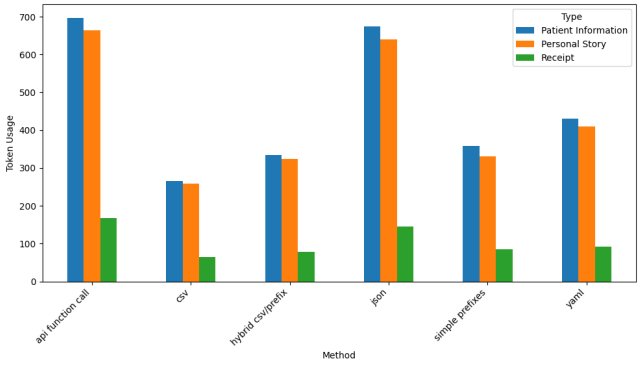

Figure 19. Claude Token Usage by Prompt Style and Type

cate that API Function Call and JSON prompt styles consume the highest number of tokens, particularly for *Patient Information* and *Personal Story* datasets, where token usage exceeds 700 tokens. This finding reflects the verbose and detailed outputs required for these structured tasks.

In contrast, the CSV and Simple Prefixes prompt styles show the lowest token usage for Claude. In particular, the *Receipt* dataset consistently shows minimal token consumption. This efficiency highlights Claude's adaptability in generating concise outputs for simpler datasets and formats.

The moderate range of token usage for the Hybrid CSV/Prefix and YAML prompt styles reveal how Claude balances verbosity and efficiency. Across all prompt styles, *Patient Information* datasets consistently require the most tokens, followed by *Personal Story*, while *Receipt* datasets remain the least token-intensive. These results show Claude's ability to balance output quality and verbosity based on dataset complexity and output requirements.

4.2.3 Time Analysis for Claude

Figure 20 shows Claude's time performance across the prompt styles and dataset types. These results indicate the

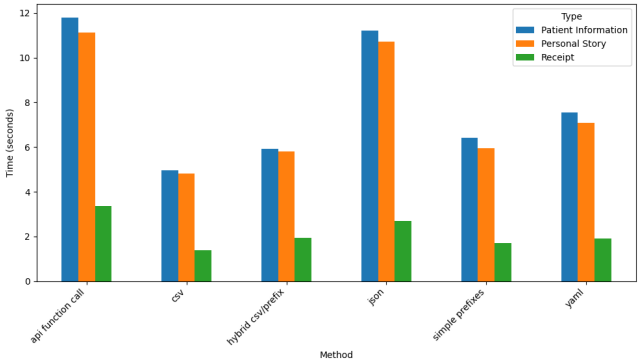

Figure 20. Claude Time Taken by Prompt Style and Type

API Function Call and JSON prompt styles require the most time for processing, with *Patient Information* datasets taking over twelve seconds on average. This finding reflects the complexity of generating detailed and structured outputs for these prompt styles and datasets.

Conversely, the CSV prompt style demonstrates the fastest processing times, particularly for the *Receipt* dataset, where times fall below 2 seconds. This efficiency highlights Claude's ability to handle simple tabular formats and transactional data effectively.

Hybrid CSV/Prefix and YAML prompt styles exhibit moderate processing times, balancing the trade-offs between complexity and efficiency. Across all prompt styles, *Patient Information* consistently requires the most processing time, followed by *Personal Story*, while *Receipt* datasets remain the fastest to process. These results underscore Claude's adaptability in balancing processing time with output complexity and dataset characteristics.

Claude's performance across the accuracy, token usage, and time metrics show its strengths in handling structured data and its limitations with narrative-style datasets. Claude achieves near-perfect accuracy for structured datasets, such as *Patient Information* and *Receipt*, regardless of the prompt style used. Its performance declines significantly, however, for the narrative-style *Personal Story* dataset, where accuracy stabilizes around 40% across prompt styles.

Claude's token usage demonstrates efficiency for simpler prompt styles like CSV and Simple Prefixes, especially for the *Receipt* dataset. It requires substantially more tokens, however, for verbose prompt styles like API Function Call and JSON, particularly for *Patient Information* and *Personal Story*.

Claude's processing times are similarly dataset-dependent, with *Patient Information* and *Personal Story* requiring the longest times for API Function Call and JSON prompt styles, which exceed twelve seconds. Conversely, simpler prompt styles like CSV and datasets like *Receipt* exhibit faster processing times, often below two seconds. These results emphasize Claude's capability for structured data tasks while revealing areas to improve its efficiency and performance for narrative or unstructured data.

4.3 Gemini Analysis of Experiment Results

This section examines the performance of the Gemini LLM across the three datasets described in Section 3.1 in accordance with the accuracy, token usage, and processing time metrics described in Section 3.2. This analysis assessed Gemini's adaptability and effectiveness in handling structured, semi-structured, and narrative data and quantified Gemini's strengths in producing structured outputs while identifying its trade-offs in computational efficiency and output quality across diverse datasets.

4.3.1 Accuracy Analysis for Gemini

Figure 21 visualizes the accuracy of Gemini across the various prompt styles and dataset types. These results in-

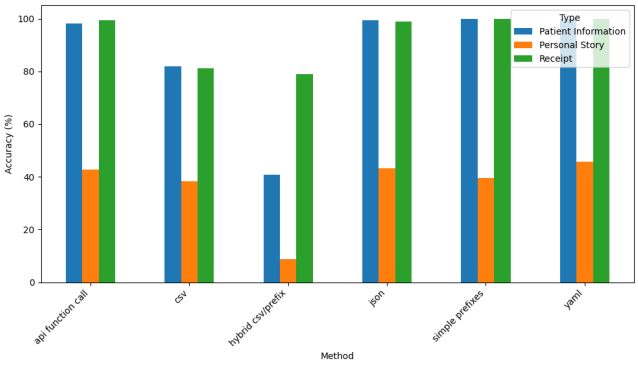

Figure 21. Gemini Accuracy by Prompt Style and Type

dicate consistently high accuracy for structured datasets like *Patient Information* and *Receipt* across most prompt styles, with scores nearing 100%. This finding demonstrates Gemini's capability to generate reliable outputs for well-structured data.

In contrast, Gemini struggled with the narrative-style *Personal Story* dataset, where accuracy stabilized at ∼40% across all prompt styles, reflecting limitations in structuring less formal, narrative inputs. Among the prompt styles, API Function Call and YAML exhibit the highest accuracy for structured datasets, while Hybrid CSV/Prefix shows a slight decline in accuracy for *Patient Information*, suggesting challenges in mixed-format data generation. Overall, Gemini displays strong adaptability to various prompt styles, excelling in structured tasks while maintaining consistent but moderate performance for narrative data.

4.3.2 Token Usage Analysis for Gemini

Figure 22 shows Gemini's token usage across various prompt styles and dataset types. These results indicate that

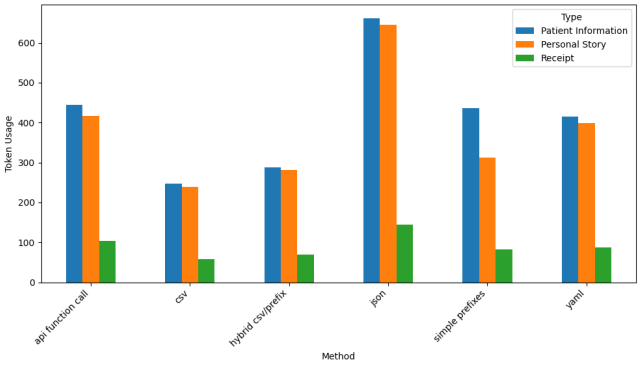

Figure 22. Gemini Token Usage by Prompt Style and Type

API Function Call and JSON prompt styles require the highest number of tokens, particularly for *Patient Information* and *Personal Story*, where token usage exceeds 500 tokens. This finding reflects the verbose and detailed outputs generated by Gemini for structured and semi-structured datasets.

In contrast, the CSV prompt style demonstrates the lowest token usage, particularly for the *Receipt* dataset, where usage remains consistently below 100 tokens. This efficiency highlights Gemini's ability to adapt its verbosity to simpler formats and transactional data.

Hybrid CSV/Prefix and YAML prompt styles fall within a moderate range of token usage, balancing output verbosity and efficiency effectively. Across all prompt styles, *Patient Information* consistently requires the most tokens, followed by *Personal Story*, while *Receipt* datasets remain the least token-intensive. These findings emphasize Gemini's ability to balance token consumption while maintaining high output quality across diverse datasets and prompt styles.

4.3.3 Time Analysis for Gemini

Figure 23 depicts Gemini's time performance across all the prompt styles and dataset types. These results show that the API Function Call prompt style requires the longest processing time across all datasets, particularly for *Personal Story*, which exceeds ten seconds. This finding reflects the additional complexity and verbosity required for narrative-style data in this prompt style.

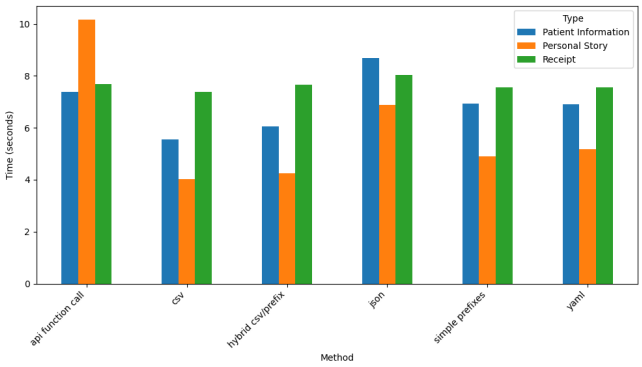

Figure 23. Gemini Time Taken by Prompt Style and Type

Conversely, the CSV and Hybrid CSV/Prefix prompt styles demonstrate the shortest processing times, especially for the *Receipt* dataset, where times consistently remain below four seconds. This finding shows Gemini's ability to handle structured and simple formats efficiently.

YAML and JSON prompt styles exhibit moderate processing times, balancing output quality and computational demand. Across all prompt styles, *Patient Information* and *Receipt* datasets display consistent performance, whereas *Personal Story* remains the most variable and often the most time-intensive. These results emphasize Gemini's efficiency for structured data and its adaptability to diverse prompt styles and dataset types.

Gemini demonstrates strong performance across the accuracy, token usage, and time metrics, with clear strengths in handling structured data and moderate adaptability for narrative-style inputs. It achieves near-perfect accuracy for structured datasets like *Patient Information* and *Receipt* across most prompt styles, while its performance for the narrative-style *Personal Story* dataset is consistent but lower, stabilizing around 40%. Gemini's token usage balances verbosity and efficiency effectively, with prompt styles like CSV and Hybrid CSV/Prefix requiring minimal tokens, particularly for simpler datasets like *Receipt*.

However, verbose prompt styles such as API Function Call and JSON exhibit higher token usage, especially for complex datasets like *Patient Information* and *Personal Story*. Processing times further reflect this trend, with API Function Call being the most time-intensive, particularly for *Personal Story* datasets. In contrast, the CSV and Hybrid CSV/Prefix prompt styles demonstrate the fastest times, especially for the *Receipt* dataset. These results highlight Gemini's adaptability and efficiency in structured data tasks, while also revealing areas for improvement in handling narrative or semi-structured data with less verbosity and faster response times.

5 Comparison of ChatGPT-4o, Claude, and Gemini LLM Models

This section provides a comparative analysis of the performance of GPT-4o, Claude, and Gemini on the three datasets described in Section 3.1. This analysis builds directly upon our prior study of prompt style efficiency using GPT-4o and three prompt formats (JSON, YAML, and Hybrid CSV/Prefix) [8]. In this extended work, we introduce three additional prompt styles (CSV, API Function Call, and Simple Prefixes) and evaluate them across three advanced LLMs. While we reuse elements of the experimental design and visualization formats (such as accuracy/token/-time comparisons), all results have been independently regenerated and expanded to support model-level comparative analysis. As before, our evaluation focuses on the accuracy, token usage, and processing time metrics to highlight the pros and cons of each LLM across various prompt styles and data types. By examining their adaptability to structured, semi-structured, and narrative datasets, this comparison quantifies unique characteristics of each LLM and identifies trade-offs between efficiency, quality, and computational demands.

5.1 Why Models Differ: Mechanistic Hypotheses and Qualitative Evidence

Our cross-model results reveal a pattern: Claude attains the highest accuracy, ChatGPT-4o is most efficient in time and tokens, and Gemini balances the two. We hypothesize the following reasons for this pattern:

- **Alignment and decoding preferences.** Claude's conservative, instruction-faithful decoding appears to favor completeness of fields (higher accuracy) at the cost of verbosity (more tokens and time).
- **Efficiency tuning.** ChatGPT-4o yields lean outputs (fewer tokens, lower latency), occasionally omitting low-salience attributes in narrative contexts, which can reduce measured attribute recall.
- **Balanced priors.** Gemini exhibits moderate verbosity and accuracy, suggesting a decoding strategy that trades a small amount of precision for efficiency across formats.

To ground these hypotheses, we reviewed representative outputs and categorized common error types into (i) *omission* (required field missing), (ii) *type/format* (value present but malformatted), and (iii) *misassignment* (value placed under the wrong key).

Preliminary inspection suggests that Claude tends to minimize *omission* errors, supporting its higher accuracy on hierarchical outputs, while ChatGPT-4o favors brevity, occasionally dropping low-salience fields in favor of token and time efficiency. Gemini balances these tendencies but shows slightly higher rates of misassignment in narrative-style tasks.

A full quantitative audit of error categories will be our focus in future work, as discussed in Section 7. Nevertheless, this taxonomy provides a mechanism-oriented lens for interpreting the observed trade-offs in accuracy and efficiency across models.

5.2 Comparing the Accuracy of ChatGPT-4o, Claude, and Gemini

The comparative accuracy performance of ChatGPT-4o, Claude, and Gemini across various prompt styles is shown in Figure 24. This figure shows that Claude is the most accurate LLM, consistently achieving accuracy levels above 80% across all prompt styles. Its ability to handle diverse input structures and datasets underscores its robustness. ChatGPT-4o also demonstrates steady performance, with accuracy levels ranging between 75% and 80%, reflecting its adaptability to various prompt styles.

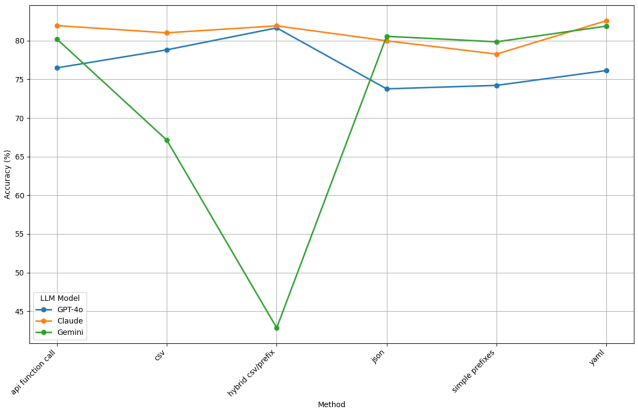

Figure 24. Accuracy Comparison Across LLMs (extended from [8])

In contrast, Gemini exhibits variable accuracy, performing well in structured prompt styles like YAML and API Function Call but showing significant declines in Hybrid CSV/Prefix, where its accuracy dips below 65%. This finding highlights potential challenges in managing mixed-style prompts for certain datasets. Among the prompt styles, API Function Call and YAML show high accuracy for all models, while Hybrid CSV/Prefix poses difficulties for Gemini. These results highlight Claude's superior versatility, ChatGPT-4o's stability, and Gemini's specialized strengths with notable areas for improvement.

5.3 Comparing the Token Usage of ChatGPT-4o, Claude, and Gemini

Figure 25 compares the token usage of ChatGPT-4o, Claude, and Gemini across various prompt styles. These results show ChatGPT-4o consistently consuming the fewest tokens across all prompt styles, underscoring its efficiency in generating concise outputs. This efficiency is particularly

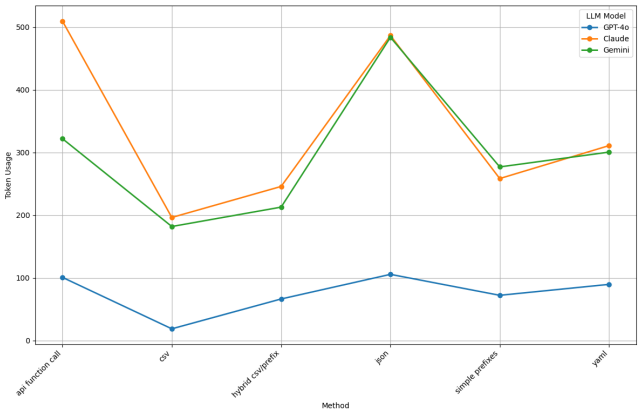

Figure 25. Token Usage Comparison Across LLMs (extended from [8])

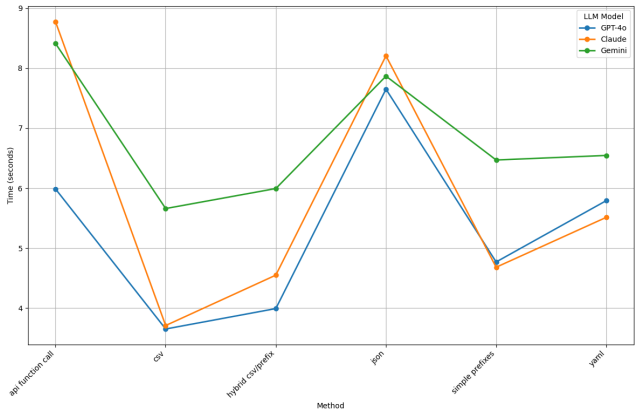

Figure 26. Time Comparison Across LLMs (extended from [8])

notable in prompt styles like CSV, Simple Prefixes, and Hybrid CSV/Prefix, where ChatGPT-4o's token usage remains much lower than Claude and Gemini's usage.

In contrast, Claude exhibits the highest token usage for most prompt styles, indicating a propensity to produce more verbose responses. This trend is particular evident in the API Function Call and JSON prompt styles, where Claude's token consumption surpasses ChatGPT-4o and Gemini by a substantial margin. Gemini positions itself between ChatGPT-4o and Claude, balancing verbosity and token efficiency, and demonstrates moderate token usage across all prompt styles.

These observations suggest that ChatGPT-4o is the most token-efficient model, which is advantageous in scenarios (such as applications with strict token limits or cost constraints) where minimizing token consumption is critical. Claude's higher token usage may be beneficial for use cases that require more detailed and elaborate responses, but could be less suitable in contexts where token economy is essential. Gemini offers a middle ground, providing a balance between detailed output and token efficiency, making it a versatile option for a variety of applications.

5.4 Comparing Time Performance of ChatGPT-4o, Claude, and Gemini

Figure 26 depicts the comparative time performance of ChatGPT-4o, Claude, and Gemini across various prompt styles. This figure shows that Claude consistently demonstrates the longest processing times, particularly for API Function Call and JSON, where times approach nine seconds. This finding reflects its detailed output generation process, which prioritizes verbosity over efficiency.

In contrast, ChatGPT-4o consistently delivers the fastest processing times across all prompt styles, maintaining a range between four and six seconds. Even for more complex prompt styles like JSON, ChatGPT-4o's time efficiency highlights its streamlined approach to output generation. Gemini exhibits variable performance, balancing efficiency for prompt styles like CSV and Hybrid CSV/Prefix while showing spikes in time for JSON, where its processing time aligns with Claude's.

For simpler prompt styles, such as CSV, all three models demonstrate shorter processing times, with ChatGPT-4o leading in efficiency. These results emphasize ChatGPT-4o's time efficiency, Claude's verbosity at the cost of longer processing times, and Gemini's balanced approach with occasional variability Figure 26.

5.5 Comparing ChatGPT-4o, Claude, and Gemini Performance Across All Metrics

A comparative analysis of ChatGPT-4o, Claude, and Gemini shows distinct trade-offs in performance across the accuracy, token usage, and time efficiency metrics. We summarize these results through two complementary visualizations, each offering unique insights into the data.

5.5.1 Metric-by-Metric Comparison Using Bar Charts

Figure 27 shows a multi-metric bar chart that extends prior visualizations [8] to enable cross-model comparisons across six prompt styles. The figure reveals clear trade-

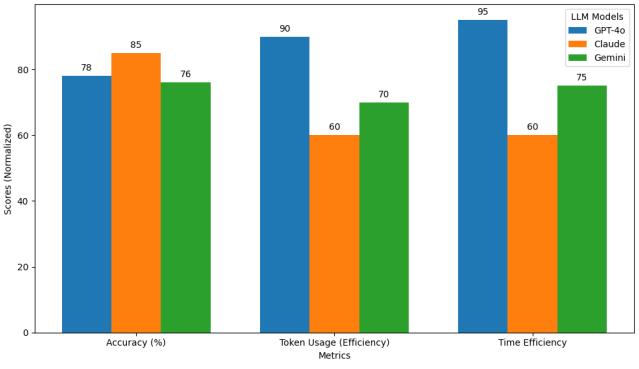

Figure 27. Metric-by-Metric Performance of ChatGPT-4o, Claude, and Gemini (extended from [8])

offs: Claude leads in accuracy (85%), particularly on complex formats like JSON and YAML; ChatGPT-4o, though slightly lower at 78%, delivers the best token and time efficiency, making it ideal for cost-sensitive tasks; and Gemini, at 76%, provides balanced but moderate results across all metrics.

5.5.2 Holistic Trade-Off Analysis Using Radar Charts

Figure 28 provides a radar chart summarizing the same metrics, offering a holistic view of the trade-offs among the three LLMs. Unlike the bar chart in Figure 27, this figure

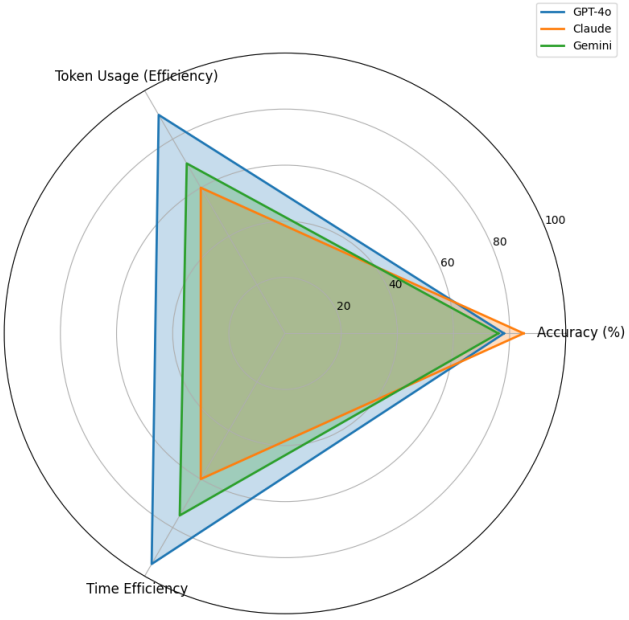

Figure 28. Aggregate Comparison of ChatGPT-4o, Claude, and Gemini Performance (extended from [8])

visualizes LLM strengths and weaknesses via a unified profile, allowing a more intuitive understanding of how each LLM balances its capabilities. For instance, Claude's focus on accuracy is visually distinct from ChatGPT-4o's dominance in token and time efficiency, whereas Gemini shows a steady but less pronounced performance across all axes.

We intentionally included both Figure 27 and 28 since each serves a different analytical purpose. The bar chart is ideal for detailed, metric-specific comparisons, enabling precise quantification of each LLM's strengths and weaknesses. In contrast, the radar chart facilitates a high-level overview, which helps stakeholders grasp LLM trade-offs quickly for practical decision-making.

5.5.3 Performance Analysis

Claude achieves the highest accuracy at 85%, particularly excelling in tasks requiring complex hierarchical representations, such as JSON and YAML prompts. This finding highlights Claude's strong ability to preserve the structural integrity of outputs. ChatGPT-4o, with an accuracy of 78%, offers consistent performance across most prompt styles but falls short of Claude's precision in highly structured outputs. While Gemini trails slightly at 76%,it exhibits competitive accuracy, showing potential for handling structured tasks effectively, but with some room for refinement.

Token efficiency places ChatGPT-4o as the most resource-efficient model, achieving a score of 90%, significantly outperforming Claude (60%) and Gemini (70%). This find demonstrates ChatGPT-4o's capability to generate concise and compact outputs while maintaining acceptable accuracy levels. Both Claude and Gemini show higher token usage, particularly in verbose formats such as JSON, indicating a trade-off between verbosity and precision.

ChatGPT-4o again emerges as the time efficiency leader with a score of 95%, delivering faster response times across a majority of prompt styles. Gemini follows with a moderate time efficiency score of 75%, balancing speed and accuracy reasonably well. Claude lags behind at 60%, reflecting its computational overhead and longer processing times, particularly for resource-intensive tasks.

5.5.4 Trade-Offs and Practical Recommendations

Our findings reveal clear trade-offs among ChatGPT-4o, Claude, and Gemini, providing practical guidance for matching models and prompt styles to application needs. Claude delivers the highest accuracy, especially in complex formats like JSON and YAML, where it excels at preserving nested hierarchies and attribute completeness. These gains, however, come with higher token costs and slower runtimes.

ChatGPT-4o offers the strongest balance of speed, efficiency, and accuracy. It consistently minimizes token usage and processing time while maintaining reliable accuracy, making it the best fit for cost-sensitive or real-time scenarios where latency and budget constraints dominate. Gemini provides steady, all-around performance, making it a flexible choice for general-purpose structured data generation. Still, its lower accuracy in styles like Hybrid CSV/Prefix and greater variability on verbose prompts suggest it may require additional tuning for specialized use cases.

This expanded multi-model trade-off analysis builds on the insights from our prior work [8], which focused on a single-model (GPT-4o) comparison. By introducing model-specific constraints and behaviors, our findings offer a more comprehensive framework for practitioners aiming to optimize structured data workflows in LLM applications.

5.5.5 Summarizing Insights in a Comparative Table

Table 1 provides a comparative analysis of ChatGPT-4o, Claude, and Gemini across key accuracy, token usage, and time efficiency metrics. This table highlights the distinct strengths and weaknesses of each LLM model when evaluated against multiple methods. Specifically, the table summarizes the overall accuracy trends, the best-performing

methods for accuracy, token usage efficiency, and time efficiency, revealing trade-offs and areas where each LLM excels or falls short.

This summary table expands upon the single-model comparison in our earlier work [8] by offering LLM-specific insights that capture model-wise trade-offs between accuracy, token cost, and time performance.

Table 1. Comparative Analysis of ChatGPT-4o, Claude, and Gemini

Metric	GPT-4o	Claude	Gemini
Accuracy (Overall)	Consistently between 75-80% across methods	Highest accuracy (>80%) across most methods	Variable; excels in YAML but struggles in Hybrid CSV/Prefix
Best Accuracy Method	API Function Call & YAML	JSON & YAML	YAML
Token Usage (Overall)	Lowest across all methods (<100 tokens)	Highest for verbose methods (>500 tokens)	Moderate token usage with spikes for JSON
Best Token Usage Method	CSV & Simple Prefixes	Hybrid CSV/Prefix	YAML
Time Efficiency	Fastest processing time (4-6 seconds)	Longest for verbose methods (7-9 seconds)	Moderate; aligns with Claude for JSON and faster for CSV

As shown in Table 1, Gemini delivers balanced performance, performing especially well with YAML and Simple Prefix prompts. Yet its lower accuracy and higher variability on Hybrid CSV/Prefix highlight the need for further tuning in mixed-format contexts. Across all three models, JSON and YAML excel at representing hierarchical data but incur heavy token costs due to verbosity. By contrast, CSV and Simple Prefix prompts are faster and more cost-efficient, though less adaptable to complex structures. The Hybrid CSV/Prefix approach aims to merge tabular clarity with prefix guidance, showing promise but inconsistent results across models.

In summary, Claude excels in accuracy for structured and verbose outputs. In contrast, ChatGPT-4o prioritizes efficiency and time, whereas Gemini offers a balanced approach while revealing areas for refinement in mixed-format tasks. These findings provide actionable insights for selecting the most suitable model and format based on specific application requirements.

6 Related Work

Recent advancements in LLMs, such as ChatGPT-4o, Claude, and Gemini, have significantly expanded their applicability to structured data generation tasks in domains like healthcare, e-commerce, and personalized content synthesis. Prior research has examined prompt engineering strategies, cross-LLM comparisons, performance metrics, and domain-specific applications. Building on these foundations, more recent work has extended findings through multi-model, multi-prompt frameworks and highlighted the importance of broader evaluation lenses, including hallucination, safety, and benchmarking rigor. This section surveys these six areas and contextualizes our contributions in relation to existing research, as shown in Figure 29.

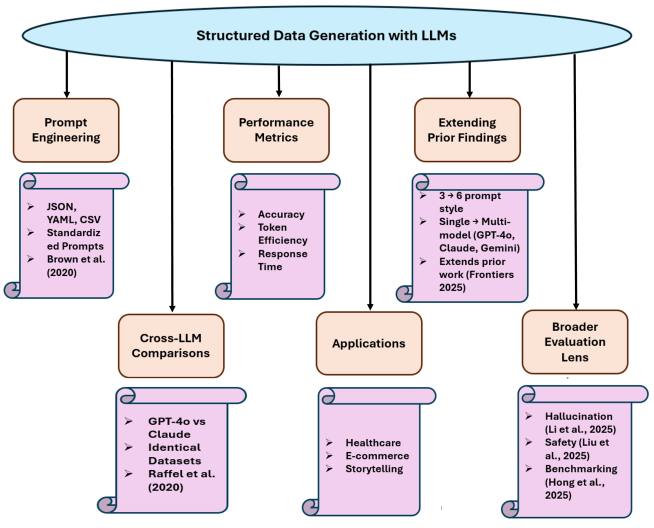

Figure 29. Structured Data Generation with LLMs (adapted from [8])

6.1 Prompt Engineering: Crafting Effective and Structured Outputs

Prompt design plays a critical role in harnessing the capabilities of LLMs to generate accurate and structured outputs. Prior studies have investigated prompt styles such as JSON, YAML, CSV, and prefix-based prompt styles, analyzing their efficacy in guiding model behavior. Notably, research by Brown et al. (2020) [6] introduced prompt-based prompt styles to instruct generative models, highlighting the importance of input formatting. Most studies tailored prompts for specific LLMs, however, potentially biasing cross-model evaluations. Our work contributes to this field by employing a standardized set of prompts across GPT-4o, Claude, and Gemini, ensuring consistency and fairness in comparative analysis.

6.2 Cross-LLM Comparisons: Evaluating LLMs Unnder Consistent Conditions

Existing work often focuses on the isolated performance of a single LLM, such as OpenAI's ChatGPT models or Anthropic's Claude. Few studies conduct direct comparisons across multiple LLMs under standardized conditions. Raffel et al. (2020) [21] compared various transformer-based models in the T5 framework, emphasizing the need for benchmark datasets to assess model robustness. Similarly, Zhang et al. (2021) [11] explored cross-model evaluations for task-specific applications but relied on tailored prompts. In contrast, our study evaluates three leading LLMs on identical datasets using consistent prompts, providing a more equitable basis for comparison.

6.3 Performance Metrics: Measuring Efficiency, Accuracy, and Cost-effectiveness

Measuring LLM performance requires a multi-faceted approach, incorporating key metrics, such as accuracy, token usage, and response time. Studies by Vaswani et al. (2017) [23] and later refinements by OpenAI [2] and Anthropic [1] emphasized token efficiency [3] as a key factor in determining LLM scalability and cost-effectiveness. Other research explored accuracy in generating structured outputs, particularly in domains like medical records and financial receipts that require hierarchical data representation. Our work extends prior research by analyzing these metrics comprehensively across diverse datasets and prompt styles, highlighting the trade-offs between verbosity, efficiency, and generation quality.

6.4 Applications of LLMs in Healthcare, E-commerce, and Storytelling

LLMs have increasingly being adopted and applied to generate structured data in domains like healthcare, personalized storytelling, and transactional record management. For instance, prior studies have demonstrated the use of LLMs in generating synthetic medical records [15] for data augmentation and training machine learning models. Similarly, e-commerce applications have leveraged LLMs for generating product descriptions [14] and receipt summaries. Our datasets, including *Personal Stories*, *Medical Records*, and *Receipt Records*, align with these use cases, enabling a realistic evaluation of LLM performance in relevant scenarios.

6.5 Extending Prior Findings Via a Multi-model, Multi-prompt Framework

Our prior work [8] focused on evaluating three prompt styles with GPT-4o. In contrast, our current study significantly expands the prompt and model space. By conducting comparative evaluations across ChatGPT-4o, Claude, and Gemini using six prompt styles, we generalize previous conclusions and identify nuanced model-specific behaviors and trade-offs. This broader framework provides a more actionable foundation for prompt design and model selection in structured data applications.

6.6 Broader Evaluation Lens

Complementary literature on hallucination [16], safety evaluation [19], and mathematical rigor in benchmarking [13] motivates richer assessment axes beyond our core triad. The considerations described in Section 7 are aligned with these lenses and provide a path to integrate safety-and-reliability perspectives into structured data generation pipelines.

7 Limitations and Future Work

Our study emphasizes three reproducible metrics (accuracy, token cost, time) on randomized, controlled datasets across three contexts. This scope omits several deployment-oriented dimensions that we plan to incorporate:

- **Robustness** to noisy instructions and distractors, including spelling errors, shuffled key orders, and extraneous tokens.
- **Graceful handling of missing fields** while preserving schema placeholders in CSV/Hybrid outputs.
- **Generalization to unseen schemas** and attribute drift common in production pipelines.

In Section 5.1, we introduced a preliminary qualitative **error taxonomy** (omission, type/format, misassignment) to interpret why models differ. While this taxonomy provides useful insights into alignment, efficiency, and trade-offs among Claude, ChatGPT-4o, and Gemini, it remains qualitative. A full *quantitative audit* of these error categories across datasets and prompt styles will be the focus of future work, providing stronger empirical grounding for the mechanistic hypotheses.

Our future work will therefore extend evaluation along broader dimensions of robustness and reliability. This includes (i) a quantitative audit of error categories introduced in Section 5.1, and (ii) expanded robustness testing (*e.g.*, noisy prompts, missing fields, and unseen schemas) to strengthen the mechanistic explanations of model behavior and provide deeper guidance for structured data generation in real-world deployments.

Finally, while randomized attributes enable controlled comparisons, they may under-represent domain-specific edge cases and regulatory constraints present in real EMR or e-commerce data. To address this, we are extending our datasets with semi-synthetic corpora curated from real schemas (de-identified) and will release scripts to reproduce robustness tests.

8 Concluding Remarks

This paper presented a detailed methodology, comprehensive analysis, and practical recommendations stemming from a study evaluating the impact of prompt styles on structured data generation tasks with LLMs. Our study results contribute to the growing body of knowledge on prompt engineering and structured data generation with LLMs. The following are lessons we learned from conducting the research presented in this paper:

- **Trade-offs in prompt design are context-dependent**. Understanding the trade-offs associated with different prompting techniques helps developers and data scientists make informed choices that balance accuracy, efficiency, and cost-effectiveness. For instance, hierarchical formats like JSON and YAML [9] offer superior accuracy but at a higher token cost, whereas CSV and simple prefixes [5] provide cost-efficient alternatives with reduced flexibility for complex structures.

- **Alternative formats deliver unique advantages**. Alternative formats, such as simple prefixes and hybrid approaches, can offer high accuracy with reduced token costs in certain use cases. These formats are less verbose and strike a balance between clarity and conciseness, making them valuable for semi-structured data, such as receipts or transactional records.
- **Consistent prompts enhances evaluation fairness**. Using consistent prompts across different LLMs ensures fairness in evaluation and highlights the inherent capabilities of each LLM. Our findings demonstrate that standardized prompts provide a reliable baseline for performance comparison to avoid biases caused by prompt tailoring for specific LLMs.
- **Efficiency gains vary across LLMs**. The study revealed significant differences in token usage and processing times among ChatGPT-4o, Claude, and Gemini. While ChatGPT-4o had the highest efficiency in both token consumption and time, Claude excelled in accuracy and Gemini struck a balance between the two. These insights guide LLM selection for specific use cases where speed or cost constraints are critical.
- **Applications influence prompt selection**. The selection of prompt styles can vary significantly based on application domain. For example, our results demonstrate how JSON and YAML formats are better suited for domains like healthcare requiring hierarchical data representation. Conversely, CSV and simple prefixes excel in domains like e-commerce where token efficiency and processing speed are critical. While our datasets simulate healthcare (*e.g.*, medical records) and e-commerce (*e.g.*, receipt records), our results generalize to similar structured data across these domains.
- **Prompt design impacts outcomes**. While our study does not focus directly on iterative prompt refinement [17], the results indicate that careful initial prompt design plays a key role in determining the accuracy and efficiency of LLM outputs. This finding underscores the importance of selecting prompt styles that align with the dataset's complexity and intended use case. Our future work will explore the role of iterative refinement in enhancing LLM output quality, which is beyond the scope of this paper.

Overall, this paper extends our earlier work [8] by expanding the prompt design space, model diversity, and evaluation depth. These contributions support a broader understanding of how LLMs can be effectively leveraged for structured data generation in real-world applications.

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We used ChatGPT-4o's code generate capabilities to visualize the data and filter the datasets. Likewise, Claude and Gemini's outputs provided a comparative evaluation of LLM performance across structured data generation tasks. The contributions of these LLMs enriched the analysis and insights presented in this study.

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