Hidden Non-Determinism in Large Language Model APIs: A Lightweight Provenance Protocol for Reproducible Generative AI Research

LUCAS ROVER*, UTFPR – Universidade Tecnológica Federal do Paraná, Brazil
YARA DE SOUZA TADANO, UTFPR – Universidade Tecnológica Federal do Paraná, Brazil

Background: Generative AI models produce non-deterministic outputs that vary across runs, even under nominally identical configurations. This variability threatens the reproducibility of studies that rely on large language model (LLM) outputs, yet most existing experiment-tracking tools were not designed for the specific challenges of text-generation workflows.

Objectives: We propose a lightweight, open-standard protocol for logging, versioning, and provenance tracking of generative AI experiments. The protocol introduces two novel documentation artifacts—Prompt Cards and Run Cards—and adopts the W3C PROV data model to create auditable, machine-readable provenance graphs linking every output to its full generation context.

Methods: We formalize the protocol and evaluate it empirically through 3,504 controlled experiments. These experiments employ five models—three locally deployed (LLaMA 3 8B, Mistral 7B, Gemma 2 9B) and two API-served (GPT-4, Claude Sonnet 4.5)—on four NLP tasks (scientific summarization, structured extraction, multi-turn refinement, and retrieval-augmented generation) across 30 scientific abstracts and five experimental conditions that systematically vary the seed, temperature, and decoding strategy. We measure output variability using Exact Match Rate, Normalized Edit Distance, ROUGE-L, and BERTScore, and quantify the protocol's own overhead in terms of time and storage.

Results: Under greedy decoding (t=0), local models achieve near-perfect reproducibility: Gemma 2 9B reaches EMR = 1.000 across all tasks, LLaMA 3 attains EMR = 0.987 for extraction, and Mistral 7B achieves EMR = 0.960. By contrast, API-served models exhibit substantial hidden non-determinism: GPT-4 achieves only EMR = 0.443 for extraction, while Claude Sonnet 4.5 achieves EMR = 0.190 for extraction and EMR = 0.020 for summarization—the lowest observed in our study. This local-vs-API reproducibility gap (average EMR: 0.960 vs. 0.158) persists across all four tasks and is confirmed across two independent API providers. Multi-turn refinement and RAG extraction maintain high reproducibility for local models (EMR ≥ 0.880). The protocol adds less than 1% overhead across all five models.

Conclusions: Our results demonstrate that (1) server-side non-determinism in API-served models—not user-controllable parameters—is the dominant source of irreproducibility, confirmed independently for both GPT-4 and Claude; (2) locally deployed models achieve near-perfect to perfect bitwise reproducibility under greedy decoding; (3) this gap persists across single-turn, multi-turn, and RAG interaction regimes; (4) temperature is the dominant user-controllable factor affecting variability; and (5) comprehensive provenance logging adds negligible overhead (<1%). The protocol, reference implementation, and all experimental data are publicly available.

CCS Concepts: • **Software and its engineering** → **Software testing and debugging**; *Documentation*; • **Computing methodologies** → **Machine learning**.

*Corresponding Author.

Authors' Contact Information: Lucas Rover, ORCID: 0000-0001-6641-9224, lucasrover@utfpr.edu.br, UTFPR – Universidade Tecnológica Federal do Paraná, Programa de Pós-Graduação em Engenharia Mecânica, Ponta Grossa, Paraná, Brazil; Yara de Souza Tadano, ORCID: 0000-0002-3975-3419, yaratadano@utfpr.edu.br, UTFPR – Universidade Tecnológica Federal do Paraná, Programa de Pós-Graduação em Engenharia Mecânica, Ponta Grossa, Paraná, Brazil.

DOI: 10.1613/jair.1.xxxxx

Additional Key Words and Phrases: reproducibility, large language models, non-determinism, provenance, generative AI, experiment tracking, W3C PROV, scientific methodology

JAIR Associate Editor: Insert JAIR AE Name

JAIR Reference Format:
Lucas Rover and Yara de Souza Tadano. 2026. Hidden Non-Determinism in Large Language Model APIs: A Lightweight Provenance Protocol for Reproducible Generative AI Research. *Journal of Artificial Intelligence Research* (2026), 27 pages. DOI: 10.1613/jair.1.xxxxx

1 Introduction

When a researcher queries a cloud-hosted LLM with the same prompt and temperature zero, one would reasonably expect identical outputs. Our experiments show otherwise: across five controlled seeds under greedy decoding, GPT-4 produces the same extraction result only 44% of the time, and Claude Sonnet 4.5 achieves only 19%. Meanwhile, locally deployed models such as Gemma 2 9B produce *perfectly identical* outputs every time. This hidden, provider-dependent non-determinism exemplifies a fundamental challenge introduced by the rapid adoption of large language models (LLMs) in scientific research: how to ensure that studies relying on generative AI outputs are reproducible, auditable, and scientifically rigorous. Unlike traditional computational experiments, in which deterministic algorithms produce identical results given identical inputs, LLMs exhibit inherent variability in their outputs due to stochastic sampling, floating-point non-determinism, and opaque model-versioning practices (Y. Chen et al. 2023; Zhu et al. 2023).

This reproducibility challenge is not merely theoretical. Baker (2016) reported that over 70% of researchers have failed to reproduce another scientist's experiment, a crisis that extends to AI research (Gundersen and Kjensmo 2018; Hutson 2018; Kapoor and A. Narayanan 2023; Stodden et al. 2016). For generative AI specifically, the problem is compounded by several factors unique to text-generation workflows: (1) the same prompt can yield semantically similar yet textually distinct outputs across runs; (2) API-based models may undergo silent updates that alter behavior; (3) temperature and sampling parameters create a high-dimensional space of possible outputs; and (4) no established standard exists for documenting the full context needed to understand, audit, or reproduce a generative output.

Existing experiment-tracking tools such as MLflow (Zaharia et al. 2018), Weights & Biases (Biewald 2020), and DVC (Kuprieiev et al. 2024) were designed primarily for training pipelines and numerical metrics. Although valuable for their intended purposes, these tools lack features critical for generative AI studies: structured prompt versioning, cryptographic output hashing for tamper detection, provenance graphs linking outputs to their full generation context, and environment fingerprinting specific to inference-time conditions.

In this paper, we make three contributions:

(1) **A lightweight protocol** for logging, versioning, and provenance tracking of generative AI experiments. The protocol introduces *Prompt Cards* and *Run Cards* as structured documentation artifacts, and adopts the W3C PROV data model (Moreau and Missier 2013) for machine-readable provenance graphs.
(2) **An empirical evaluation** of both the protocol's effectiveness and the reproducibility characteristics of LLM outputs. Through 3,504 controlled experiments with five models—three locally deployed (LLaMA 3 8B, Mistral 7B, Gemma 2 9B) and two API-served (GPT-4, Claude Sonnet 4.5)—across four tasks (extraction, summarization, multi-turn refinement, RAG extraction), 30 abstracts, and five conditions, we quantify output variability using four complementary metrics and measure the protocol's overhead. Our results document a striking, provider-independent reproducibility gap between local and API-based inference that is invisible without systematic logging.
(3) **A reference implementation** in Python that demonstrates the protocol's practical applicability, together with all experimental data, to facilitate adoption and independent verification.

The remainder of this paper is organized as follows. Section 2 reviews related work on reproducibility in AI and experiment tracking. Section 3 formalizes the protocol design. Section 4 describes the experimental methodology. Section 5 presents the empirical results. Section 6 discusses findings, limitations, and practical implications. Section 7 concludes with directions for future work.

2 Related Work

2.1 Reproducibility in AI Research

The reproducibility crisis in AI has been documented extensively. Gundersen and Kjensmo (2018) surveyed 400 AI papers and found that only 6% provided sufficient information for full reproducibility. Pineau et al. (2021) reported on the NeurIPS 2019 Reproducibility Program, which introduced reproducibility checklists and found significant gaps between reported and actual reproducibility. More recently, Gundersen, Helmert, et al. (2024) described four institutional mechanisms adopted by JAIR—reproducibility checklists, structured abstracts, badges, and reproducibility reports—establishing a community standard for what should be documented in AI research. Gundersen, Gil, et al. (2018) identified three levels of reproducibility in AI—method, data, and experiment—and argued that all three are necessary for scientific progress. Belz et al. (2021) conducted a systematic review of 601 NLP papers and confirmed pervasive under-reporting of experimental details, while Dodge et al. (2019) proposed improved reporting standards for ML experiments, including confidence intervals and significance tests across multiple runs. More broadly, Kapoor and A. Narayanan (2023) identified data leakage as a widespread driver of irreproducible results across 17 scientific fields that use ML-based methods.

For generative AI specifically, Y. Chen et al. (2023) demonstrated that ChatGPT's outputs on NLP benchmarks exhibit non-trivial variability across identical queries, even with temperature set to zero. Zhu et al. (2023) showed that reproducibility degrades further when tasks involve subjective judgment, such as social computing annotations. Most recently, Atil et al. (2024) systematically measured the non-determinism of five LLMs under supposedly deterministic settings across eight tasks, finding accuracy variations up to 15% across runs and introducing the Total Agreement Rate (TAR) metric. Ouyang et al. (2024) confirmed that temperature zero does not guarantee determinism in ChatGPT code generation. Most recently, Yuan et al. (2025) traced such non-determinism to numerical precision issues in GPU kernels and proposed LayerCast as a mitigation strategy. Our work complements these studies in four specific ways. First, whereas prior studies (including Atil et al.'s five-model, eight-task study) measure variability post hoc, we provide a structured provenance protocol that enables *prospective* documentation and audit—answering not only "how much variability?" but also "why did these outputs differ?" through cryptographic hashing and W3C PROV graphs. Second, we directly compare local and API-based inference on identical tasks with identical prompts across *five* models and *two* independent API providers (OpenAI and Anthropic), isolating the deployment paradigm as a variable and confirming that API non-determinism is systemic rather than provider-specific. Third, we extend beyond single-turn evaluation to include multi-turn refinement and retrieval-augmented generation, demonstrating that reproducibility characteristics generalize across interaction regimes. Fourth, we quantify the overhead of systematic logging, demonstrating that the "cost of knowing" is negligible.

2.2 Experiment Tracking Tools

Several tools exist for tracking machine learning experiments, although none was designed specifically for generative AI text-output workflows:

MLflow (Zaharia et al. 2018) provides experiment tracking, model packaging, and deployment. It logs parameters, metrics, and artifacts, but focuses on training pipelines and numerical outcomes rather than text-generation provenance.

Table 1. Comparison of our protocol with existing reproducibility tools and frameworks for GenAI experiments. Checkmarks (✓) indicate full support; tildes (~) indicate partial support; dashes (–) indicate no support.

Feature	Ours	MLflow	W&B	DVC	OpenAI Evals	LangSmith
Prompt versioning (Prompt Card)	✓	–	~	–	~	~
Run-level provenance (W3C PROV)	✓	–	–	–	–	–
Cryptographic output hashing	✓	–	–	✓	–	–
Seed & param logging	✓	✓	✓	–	✓	✓
Environment fingerprinting	✓	~	~	~	–	–
Model weights hashing	✓	–	~	✓	–	–
Overhead <1% of inference	✓	~	~	N/A	N/A	~
Designed for GenAI text output	✓	–	–	–	✓	✓
Open standard (PROV-JSON)	✓	–	–	–	–	–
Local-first (no cloud dependency)	✓	✓	–	✓	–	–

Weights & Biases (Biewald 2020) offers experiment tracking with visualization dashboards. It supports prompt logging but lacks structured prompt versioning, cryptographic output hashing, and provenance graph generation.

DVC (Kuprieiev et al. 2024) provides data versioning through git-like operations. While effective for dataset management, it does not address run-level provenance or prompt documentation.

OpenAI Evals (OpenAI 2023) is a framework for evaluating LLM outputs against benchmarks. It provides structured evaluation but is tightly coupled to OpenAI's ecosystem and does not generate interoperable provenance records.

LangSmith (LangChain 2023) offers tracing and evaluation for LLM applications. It captures detailed execution traces but uses a proprietary format and requires cloud connectivity.

More broadly, Bommasani et al. (2022) identified reproducibility as a key risk for foundation models, and Liang et al. (2023) proposed the HELM benchmark for holistic evaluation of language models, including robustness and fairness dimensions that complement our reproducibility focus. In the provenance space, Padovani et al. (2025) recently introduced yProv4ML, a framework that captures ML provenance in PROV-JSON format with minimal code modifications; our protocol shares the commitment to W3C PROV but targets the specific challenges of stochastic text generation rather than training pipelines.

Table 1 provides a systematic feature-by-feature comparison of our protocol with these tools. The key distinction is not merely one of tooling but of *scientific capability*: existing tools log what happened during training (parameters, metrics, artifacts), whereas our protocol enables answering questions that these tools cannot—specifically, whether two generative outputs are provably derived from identical configurations, which exact factor caused a divergence between non-identical outputs, and whether an output has been tampered with post-generation. These capabilities require the combination of cryptographic hashing, structured prompt documentation, and W3C PROV provenance graphs that no existing tool provides. In short, our contribution is not an alternative experiment tracker but a *reproducibility assessment framework* designed for the unique challenges of stochastic text generation.

2.3 Provenance in Scientific Computing

Data provenance—the lineage of data through transformations—has a rich history in database systems and scientific workflows (Herschel et al. 2017). The W3C PROV family of specifications (Moreau and Missier 2013) provides a standardized data model for representing provenance as directed acyclic graphs of *entities*, *activities*, and *agents*. Samuel and König-Ries (2022) applied provenance tracking to computational biology workflows, demonstrating its value for reproducibility. However, to our knowledge, no prior work has applied W3C PROV specifically to generative AI experiment workflows, in which the challenge involves not only tracking data lineage but also capturing the stochastic generation context that determines output variability.

Taken together, these gaps point to a clear need: a lightweight, standards-based protocol that bridges generative AI inference with the provenance infrastructure already established in scientific computing. The next section presents our design for such a protocol.

3 Protocol Design

Our protocol addresses the question: *What is the minimum set of metadata that must be captured for each generative AI run to enable auditing, reproducibility assessment, and provenance tracking?* We address this question through four complementary components.

3.1 Scope and Design Principles

The protocol is designed around three principles:

(1) **Completeness**: Every factor that can influence a generative output must be captured—prompt text, model identity and version, inference parameters, environment state, and timestamps.
(2) **Negligible overhead**: The logging process must not materially affect the experiment. We target <1% overhead relative to inference time.
(3) **Interoperability**: All artifacts are stored in open, machine-readable formats (JSON, PROV-JSON), aligned with the FAIR (Findable, Accessible, Interoperable, Reusable) principles (Wilkinson et al. 2016), to enable tool integration and long-term preservation.

3.2 Prompt Cards

A *Prompt Card* is a versioned documentation artifact that captures the design rationale and metadata for a prompt template used in experiments. Each Prompt Card contains:

- `prompt_id`: Unique identifier
- `prompt_hash`: SHA-256 hash of the prompt text, enabling tamper detection
- `version`: Semantic version number
- `task_category`: Classification of the task (e.g., summarization, extraction)
- `objective`: Natural-language description of what the prompt is designed to achieve
- `assumptions`: Explicit assumptions about inputs and expected behavior
- `limitations`: Known limitations or failure modes
- `target_models`: Models for which the prompt was designed and tested
- `expected_output_format`: Description of the expected output structure
- `interaction_regime`: Single-turn, multi-turn, or chain-of-thought
- `change_log`: History of modifications

Prompt Cards serve two purposes: they document design intent (supporting human understanding) and they provide a citable, hashable reference for automated provenance tracking. The concept draws inspiration from Model Cards (Mitchell et al. 2019), Datasheets for Datasets (Gebru et al. 2021), and model info sheets for reproducibility assessment (Kapoor and A. Narayanan 2023), extending the structured-documentation paradigm to the prompt layer of the generative AI pipeline.

3.3 Run Cards

A *Run Card* captures the complete execution context of a single generative AI run. Each Run Card records 24 core fields organized into five groups (the complete JSON schema in Appendix B includes these fields plus additional metadata such as `researcher_id`, `affiliation`, `system_logs`, and `errors`):

(1) **Identification**: `run_id`, `task_id`, `task_category`, `prompt_hash`, `prompt_text`
(2) **Model context**: `model_name`, `model_version`, `weights_hash`, `model_source`
(3) **Parameters**: `inference_params` (temperature, top_p, top_k, max_tokens, seed, decoding_strategy), `params_hash`
(4) **Input/Output**: `input_text`, `input_hash`, `output_text`, `output_hash`, `output_metrics`
(5) **Execution metadata**: `environment` (OS, architecture, Python version, hostname), `environment_hash`, `code_commit`, timestamps (start/end), `execution_duration_ms`, `logging_overhead_ms`, `storage_kb`

The separation of logging overhead from execution time is deliberate: it allows researchers to verify that the protocol itself does not confound experimental measurements.

3.4 W3C PROV Integration

Each experimental group (defined by a unique model–task–condition–abstract combination) is automatically translated into a W3C PROV-JSON document (Moreau and Missier 2013) that expresses the generation provenance as a directed graph. The mapping defines:

- **Entities**: Prompt, InputText, ModelVersion, InferenceParameters, Output, ExecutionMetadata
- **Activities**: RunGeneration (the inference execution)
- **Agents**: Researcher, SystemExecutor (the execution environment)

PROV relations capture the causal structure:

- `used`: RunGeneration used Prompt, InputText, ModelVersion, InferenceParameters
- `wasGeneratedBy`: Output wasGeneratedBy RunGeneration
- `wasAssociatedWith`: RunGeneration wasAssociatedWith Researcher, SystemExecutor
- `wasAttributedTo`: Output wasAttributedTo Researcher
- `wasDerivedFrom`: Output wasDerivedFrom InputText

This standardized representation enables automated reasoning about experiment provenance, including detecting when two runs share identical configurations and identifying the specific factors that differ between non-identical outputs. An abbreviated example document is given in Appendix C.

3.5 Reproducibility Checklist

We provide a 15-item checklist organized into four categories—Prompt Documentation, Model and Environment, Execution and Output, and Provenance—that researchers can use to self-assess the reproducibility of their generative AI studies. The complete checklist is provided in Appendix A.

3.6 Extensions for Advanced Workflows

The protocol's field schema accommodates complex workflows through optional extension fields. Our empirical evaluation exercises two of these extensions—multi-turn dialogues and RAG—while the remaining extensions are specified in the reference implementation's schema:

- **Multi-turn dialogues:** A `conversation_history_hash` field and `turn_index` enable linking each turn to the full conversation state. *Evaluated in Task 3 (multi-turn refinement) using Ollama's* `/api/chat` *endpoint.*

- **RAG:** Fields for retrieval context (with hashes) trace which external information influenced the output. *Evaluated in Task 4 (RAG extraction) with prepended context passages.*
- **Tool use and function calling:** Fields for available tools, tool calls (with arguments, results, and hashes) capture the full tool-use chain.
- **Chain-of-thought / agent workflows:** A `parent_run_id` field supports hierarchical provenance graphs for multi-step reasoning chains.

Having defined the protocol's components, we now evaluate it empirically along two dimensions: the reproducibility characteristics it reveals across different models and conditions, and the overhead it imposes on the experimental workflow.

4 Experimental Setup

We designed a controlled experiment to simultaneously evaluate (a) the reproducibility characteristics of LLM outputs under varying conditions and (b) the overhead imposed by our logging protocol.

4.1 Models and Infrastructure

We evaluate five models representing two fundamentally different deployment paradigms: three locally deployed open-weight models and two cloud API-served proprietary models. All local models were served through Ollama v0.15.5 (Ollama 2024) on an Apple M4 system with 24 GB unified memory running macOS 14.6 with Python 3.14.3.

4.1.1 Local Models. **LLaMA 3 8B** (Grattafiori et al. 2024): An open-weight model in Q4_0 quantization. Local deployment provides complete control over the execution environment, eliminating confounding factors such as network latency, server-side batching, and silent model updates. The model's SHA-256 weights hash was recorded per run via the Ollama API.

Mistral 7B (Jiang et al. 2023): An open-weight model (Q4_0 quantization) with a sliding-window attention mechanism, providing a second data point for local inference reproducibility at a similar parameter scale.

Gemma 2 9B (Gemma Team et al. 2024): Google's open-weight model (Q4_0 quantization), representing a third local model from an independent model family. Gemma 2 proved to be the most deterministic model in our study.

4.1.2 API-Served Models. **GPT-4** (Achiam et al. 2023): Accessed via the OpenAI API (`openai` Python SDK v1.59.9) with controlled seed parameters. The API returned `gpt-4-0613` as the resolved model version in all runs. The API introduces additional sources of variability: load balancing, server-side batching, potential model-version updates, and floating-point non-determinism across different hardware.

Claude Sonnet 4.5 (Anthropic 2024): Accessed via the Anthropic API using a lightweight `urllib`-based runner (no SDK dependency). Claude's API does not support a `seed` parameter; we set `temperature=0` for greedy decoding and logged a seed value for protocol parity (marked as `logged-only-not-sent-to-api`). This provides an independent replication of the API non-determinism phenomenon on a second cloud provider.

4.2 Tasks

We evaluate four tasks that span the output-structure spectrum and interaction complexity:

Task 1: Scientific Summarization. Given a scientific abstract, produce a concise summary in exactly three sentences covering the main contribution, methodology, and key quantitative result. This is an open-ended generation task in which the model has considerable freedom in word choice and phrasing.

Task 2: Structured Extraction. Given a scientific abstract, extract five fields (objective, method, key_result, model_or_system, benchmark) into a JSON object. This is a constrained generation task in which the output format is fixed and the model must select, rather than generate, content.

Table 2. Experimental design: conditions, parameters, and expected outcomes.

Cond.	Description	Temp.	Seed	Reps	Expected Outcome
C1	Fixed seed, greedy	0.0	42 (fixed)	5	Deterministic output
C2	Variable seeds, greedy	0.0	5 different	5	Near-deterministic
$C3_{t=0.0}$	Temp. baseline	0.0	per-rep	3	Deterministic
$C3_{t=0.3}$	Low temperature	0.3	per-rep	3	Low variability
$C3_{t=0.7}$	High temperature	0.7	per-rep	3	High variability

Note: Tasks 1–2 are evaluated under all five conditions (C1, C2, C3). Tasks 3–4 (multi-turn, RAG) are evaluated under C1 only for the three local models. Total: 3,504 logged runs across 5 models. For API-served models, C2 uses the same fixed seed as C1; the seed parameter is advisory and does not guarantee determinism.

Task 3: Multi-turn Refinement. A three-turn dialogue in which the model first extracts structured information, then receives feedback requesting more detail, and finally produces a refined extraction. This tests reproducibility under conversational state accumulation, using Ollama's `/api/chat` endpoint for local models.

Task 4: RAG Extraction. The same structured extraction task as Task 2, but with an additional retrieved context passage prepended to the input. This tests whether augmenting the prompt with external context affects reproducibility.

4.3 Input Data

We use 30 widely-cited scientific abstracts from landmark AI/ML papers, including Vaswani et al. (2017) (Transformer), Devlin et al. (2019) (BERT), Brown et al. (2020) (GPT-3), Raffel et al. (2020) (T5), Wei et al. (2022) (Chain-of-Thought), as well as seminal works on GANs, ResNets, VAEs, LSTMs, CLIP, DALL-E 2, Stable Diffusion, LLaMA, InstructGPT, PaLM, and others. These abstracts vary in length (74–227 words), technical complexity, and the number of quantitative results reported, thereby providing substantial diversity in the generation challenge.

4.4 Experimental Conditions

We define five conditions (Table 2) that systematically vary the factors hypothesized to affect reproducibility:

Design principle for API models. For cloud-hosted APIs whose `seed` parameter is advisory rather than deterministic (as documented by OpenAI for GPT-4) or entirely absent (as with Claude), the fixed-vs.-variable seed distinction has no guaranteed effect server-side. We therefore treat C2 as the primary test of determinism under greedy decoding for such models.

C1 (Fixed seed, greedy decoding): Temperature = 0, seed = 42 for all 5 repetitions. This represents the maximum-control condition and should yield deterministic outputs.

C2 (Variable seeds, greedy decoding): Temperature = 0, seeds = {42, 123, 456, 789, 1024}. This condition tests whether seed variation affects outputs when greedy decoding is used.

C3 (Temperature sweep): Three sub-conditions at $t \in \{0.0, 0.3, 0.7\}$ with 3 repetitions each, using different seeds per repetition. This condition characterizes how temperature affects output variability.

Run counts. For Tasks 1–2 (extraction and summarization), each model is evaluated under C1 (5 runs), C2 (5 runs), and C3 (9 runs = 3 temperatures × 3 reps) per abstract. LLaMA 3 uses 30 abstracts (1,140 runs); the newer models (Mistral 7B, Gemma 2 9B, Claude Sonnet 4.5) use 10 abstracts (380 runs each). For GPT-4, quota exhaustion limited collection to 724 runs (C2: 300/300; C3: 416/450; C1: 8/300 excluded). For Tasks 3–4 (multi-turn and RAG), the three local models are evaluated under C1 with 10 abstracts × 5 repetitions = 50 runs each (300 runs total). **Grand total: 3,504 valid runs.**

Table 3 summarizes the per-model run distribution.

Table 3. Run distribution across models and tasks.

Model	Tasks 1–2	Tasks 3–4	Total
LLaMA 3 8B	1,140	100	1,240
Mistral 7B	380	100	480
Gemma 2 9B	380	100	480
GPT-4	724	—	724
Claude Sonnet 4.5	380	—	380
Chat-format control†	200	—	200
Total	**3,204**	**300**	**3,504**[1]

†LLaMA 3 8B via `/api/chat` endpoint (Appendix E).

4.5 Metrics

We adopt an operational definition of reproducibility at three levels, each mapped to a specific metric:

- **Exact reproducibility** (string-level): Two outputs are identical character-by-character. Measured by *Exact Match Rate (EMR)*.
- **Near reproducibility** (edit-level): Two outputs differ only in minor surface variations (punctuation, whitespace, synonym substitution). Measured by *Normalized Edit Distance (NED)*.
- **Semantic reproducibility** (meaning-level): Two outputs convey the same information despite different phrasing. Measured by *ROUGE-L F1* and *BERTScore F1*.

This three-level framework allows us to distinguish between outputs that are bitwise identical (EMR = 1), textually close (NED < 0.05), and semantically equivalent (ROUGE-L > 0.90). All variability metrics are computed over all $\binom{n}{2}$ unique output pairs within each experimental group (defined by model, task, condition, and abstract):

Exact Match Rate (EMR): The fraction of output pairs that are character-for-character identical. EMR = 1.0 indicates perfect reproducibility; EMR = 0.0 indicates that no two outputs match exactly.

Normalized Edit Distance (NED): The Levenshtein edit distance (Levenshtein 1966) between each pair, normalized by the length of the longer string. NED = 0.0 indicates identical outputs; higher values indicate greater textual divergence.

ROUGE-L F1: The F1 score based on the longest common subsequence at the word level (Lin 2004). This captures semantic similarity even when surface forms differ. ROUGE-L = 1.0 indicates identical word sequences.

Our primary metrics (EMR, NED, ROUGE-L) focus on exact and near reproducibility, which are the most direct measures for our research question. To complement these surface-level metrics, we also compute **BERTScore F1** (T. Zhang et al. 2020)—an embedding-based semantic similarity metric—for all conditions. BERTScore captures meaning-level equivalence that surface metrics may miss (e.g., paraphrases), providing a fourth perspective on reproducibility. For the structured extraction task, we additionally report **JSON validity rate**, **schema compliance rate**, and **field-level accuracy**, which measure whether outputs are syntactically valid JSON, contain all expected fields, and agree on individual field values across runs, respectively (see Appendix D for detailed results).

For protocol overhead, we measure:

- **Logging time**: Wall-clock time spent on hashing, metadata collection, and file I/O, measured separately from inference time.

[1] One Claude run (0.03%) returned an empty output due to API timeout and is excluded from variability metrics.

Table 4. Exact Match Rate (EMR) under greedy decoding (t=0) across five models and two tasks. Higher is more reproducible. Local models achieve near-perfect bitwise reproducibility while API-served models exhibit substantial hidden non-determinism.

Model	Source	Extraction	Summarization	N Runs	N Abstracts
Gemma 2 9B	Local	1.000	1.000	100	10
Mistral 7B	Local	0.960	0.840	100	10
LLaMA 3 8B	Local	0.987	0.931	400	30
GPT-4	API	0.443	0.230	300	30
Claude Sonnet 4.5	API	0.190	0.020	99	10

Table 5. Three-level reproducibility assessment under greedy decoding (t=0). L1: bitwise identity (EMR), L2: surface similarity (NED, ROUGE-L), L3: semantic equivalence (BERTScore F1). Values are means across abstracts.

		L1: Bitwise		L2: Surface		L3: Semantic
Model	**Task**	**EMR**	σ	**NED↓**	**ROUGE-L↑**	**BERTScore F1↑**
Gemma 2 9B	Extraction	1.000	0.000	0.000	1.000	1.0000
	Summarization	1.000	0.000	0.000	1.000	1.0000
Mistral 7B	Extraction	0.960	0.120	0.001	1.000	0.9999
	Summarization	0.840	0.196	0.046	0.955	0.9935
LLaMA 3 8B	Extraction	0.987	0.072	0.003	0.997	0.9997
	Summarization	0.931	0.157	0.014	0.986	0.9979
GPT-4	Extraction	0.443	0.335	0.072	0.938	0.9904
	Summarization	0.230	0.193	0.137	0.870	0.9839
Claude Sonnet 4.5	Extraction	0.190	0.291	0.101	0.904	0.9878
	Summarization	0.020	0.040	0.242	0.764	0.9704

- **Storage**: Size of each run record (JSON) and total storage for all protocol artifacts.
- **Overhead ratio**: Logging time as a percentage of total execution time.

5 Results

5.1 Reproducibility Under Greedy Decoding

Table 4 presents the headline result: Exact Match Rates under greedy decoding for all five models. Table 5 provides the full three-level reproducibility assessment.

5.1.1 Local Models: Near-Perfect to Perfect Reproducibility. **Finding 1: Gemma 2 9B achieves perfect bitwise reproducibility under greedy decoding.** Across all tasks and conditions with t=0, Gemma 2 9B produces EMR = 1.000 with NED = 0.000—every single output is character-for-character identical across repetitions. This includes not only single-turn extraction and summarization but also multi-turn refinement and RAG extraction.

Finding 2: All three local models achieve high reproducibility. LLaMA 3 8B attains EMR = 0.987 for extraction and 0.931 for summarization; Mistral 7B achieves 0.960 and 0.840, respectively. The small deviations from perfect reproducibility in LLaMA 3 and Mistral 7B are attributable to a warm-up effect on the first inference call after model loading, which affects 2–4 of the 10–30 abstracts per model. Seed variation (C1 vs. C2) has *no*

Table 6. API-served vs. locally deployed models under greedy decoding. Values are averaged across tasks and abstracts. Local models exhibit dramatically higher bitwise reproducibility, confirming that server-side non-determinism—not user-controllable parameters—is the primary source of variability in API-served models.

Deployment	EMR↑	NED↓	ROUGE-L↑	BS-F1↑
Local (3 models)	0.960	0.008	0.992	0.9989
API (2 models)	0.158	0.148	0.858	0.9822

Table 7. Effect of sampling temperature on Exact Match Rate (EMR). Temperature is the dominant user-controllable variability factor across all models. At t=0.7, all models achieve EMR=0 for summarization.

Model	Task	t=0.0	t=0.3	t=0.7
Gemma 2 9B	Extraction	1.000	0.200	0.033
	Summarization	1.000	0.000	0.000
Mistral 7B	Extraction	0.933	0.133	0.000
	Summarization	0.733	0.000	0.000
LLaMA 3 8B	Extraction	0.978	0.211	0.000
	Summarization	0.911	0.000	0.000
GPT-4	Extraction	0.381	0.143	0.000
	Summarization	0.144	0.000	0.000
Claude Sonnet 4.5	Extraction	0.067	0.700	0.133
	Summarization	0.000	0.233	0.033

effect under greedy decoding for any local model: the model always selects the highest-probability token, making the seed irrelevant.

5.1.2 API-Served Models: Substantial Hidden Non-Determinism. **Finding 3: Both API-served models exhibit substantial non-determinism under greedy decoding, confirmed across two independent providers.** Under t=0 with controlled seeds, GPT-4 achieves EMR = 0.443 for extraction and 0.230 for summarization. Claude Sonnet 4.5 is even less deterministic: EMR = 0.190 for extraction and EMR = 0.020 for summarization—meaning that across 10 abstracts × 5 repetitions, Claude produced the same summarization output only 2% of the time.

Table 6 summarizes the deployment-paradigm gap.

The average greedy-decoding EMR across all greedy conditions is **0.960 for local models** vs. **0.158 for API models**—a 6× reproducibility gap. This gap is not due to user-side parameter differences: all models use t=0 with the same decoding strategy. The observed variability is consistent with deployment-side factors invisible to the researcher: hardware-level floating-point non-determinism, server-side batching, and potential model routing. Crucially, this finding is now confirmed across two independent API providers (OpenAI and Anthropic), ruling out provider-specific implementation as the sole explanation and establishing server-side non-determinism as a *systemic* property of cloud-hosted LLM inference. *Without systematic logging, this non-determinism would be entirely invisible.*

5.1.3 Temperature Effects Across Models. **Finding 4: Temperature is the dominant *user-controllable* factor affecting variability.** Figure 1 shows the relationship between temperature and EMR for all five models. Table 7 provides the full temperature sweep data.

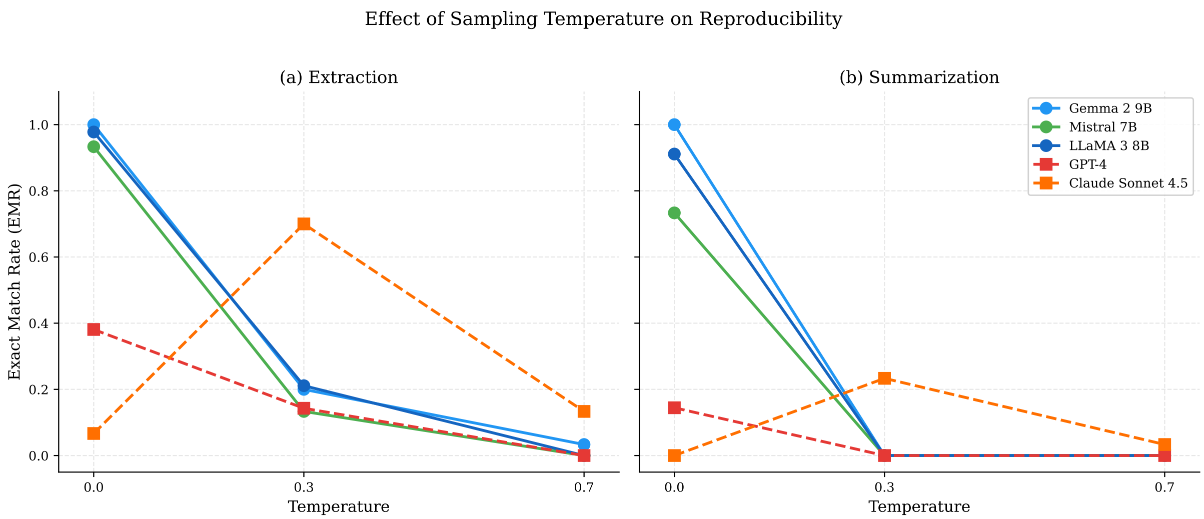

Fig. 1. Effect of temperature on Exact Match Rate across five models. (a) Extraction task. (b) Summarization task. Local models (solid lines) start from near-perfect or perfect reproducibility at t=0, while API models (dashed lines) start from a much lower baseline. All models converge toward EMR = 0 at t=0.7.

Within the C3 temperature sweep, increasing temperature from 0.0 to 0.7 reduces EMR to zero for all models on summarization. For extraction, local models drop from EMR > 0.93 to near zero, while API models drop from their already-low baselines. Notably, BERTScore F1 remains above 0.94 across all conditions even when EMR drops to zero, confirming that non-determinism is primarily a *phrasing* phenomenon rather than a *meaning* phenomenon.

5.2 Multi-Turn and RAG Reproducibility

Finding 5: Complex interaction regimes maintain high reproducibility for local models. Table 8 and Figure 2 present results for multi-turn refinement and RAG extraction.

Gemma 2 9B and Mistral 7B achieve perfect EMR = 1.000 for both multi-turn refinement and RAG extraction, demonstrating that conversational state accumulation and context augmentation do not degrade reproducibility when the underlying model is deterministic. LLaMA 3 8B shows EMR = 0.880 for multi-turn and 0.960 for RAG—slightly lower than its single-turn extraction performance (0.987), consistent with error accumulation across dialogue turns.

5.3 Cross-Model Comparison

Figure 3 provides a comprehensive heatmap of EMR across all model-task combinations, and Figure 4 shows the three-level reproducibility profile for each model.

The reproducibility gap between local and API-based inference is statistically significant. Using paired t-tests on per-abstract EMR values under greedy decoding across the 30 LLaMA 3/GPT-4 abstracts: for summarization, $t(29) = 17.250$, $p < 0.0001$, Cohen's $d = 3.149$; for extraction, $t(29) = 8.996$, $p < 0.0001$, Cohen's $d = 1.642$. Both effect sizes are very large ($d > 1.6$), and all p-values survive Bonferroni correction. Non-parametric Wilcoxon signed-rank tests confirm all results ($p < 0.001$).

Table 8. Reproducibility under complex interaction regimes (C1 fixed seed, t=0). Multi-turn refinement involves three successive prompt–response exchanges. RAG extraction augments the prompt with a retrieved context passage.

Model	Scenario	EMR	NED↓	ROUGE-L↑	BS-F1↑
Gemma 2 9B	Single-turn Extraction	1.000	0.000	1.000	1.0000
	Single-turn Summarization	1.000	0.000	1.000	1.0000
	Multi-turn Refinement	1.000	0.000	1.000	1.0000
	RAG Extraction	1.000	0.000	1.000	1.0000
Mistral 7B	Single-turn Extraction	0.960	0.001	1.000	0.9999
	Single-turn Summarization	0.840	0.046	0.955	0.9935
	Multi-turn Refinement	1.000	0.000	1.000	1.0000
	RAG Extraction	1.000	0.000	1.000	1.0000
LLaMA 3 8B	Single-turn Extraction	0.987	0.003	0.997	0.9997
	Single-turn Summarization	0.931	0.014	0.986	0.9979
	Multi-turn Refinement	0.880	0.012	0.988	0.9986
	RAG Extraction	0.960	0.012	0.985	0.9987

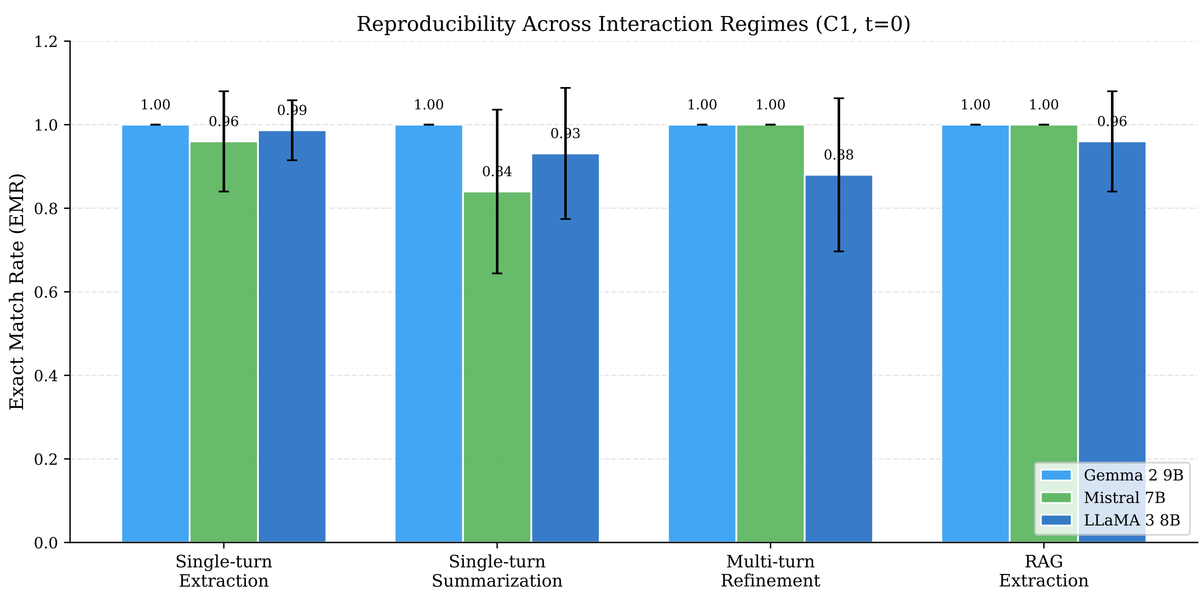

Fig. 2. Reproducibility across interaction regimes (C1, t=0) for the three local models. Gemma 2 9B and Mistral 7B maintain perfect reproducibility (EMR = 1.000) across all scenarios, while LLaMA 3 8B shows slight degradation in multi-turn refinement (EMR = 0.880).

5.4 Protocol Overhead

Table 9 presents the protocol's overhead metrics across all five models.

The protocol adds less than 1% overhead for all five models, with mean logging time ranging from 21–30 ms depending on the model and task. Storage overhead remains modest at approximately 4 KB per run record. The

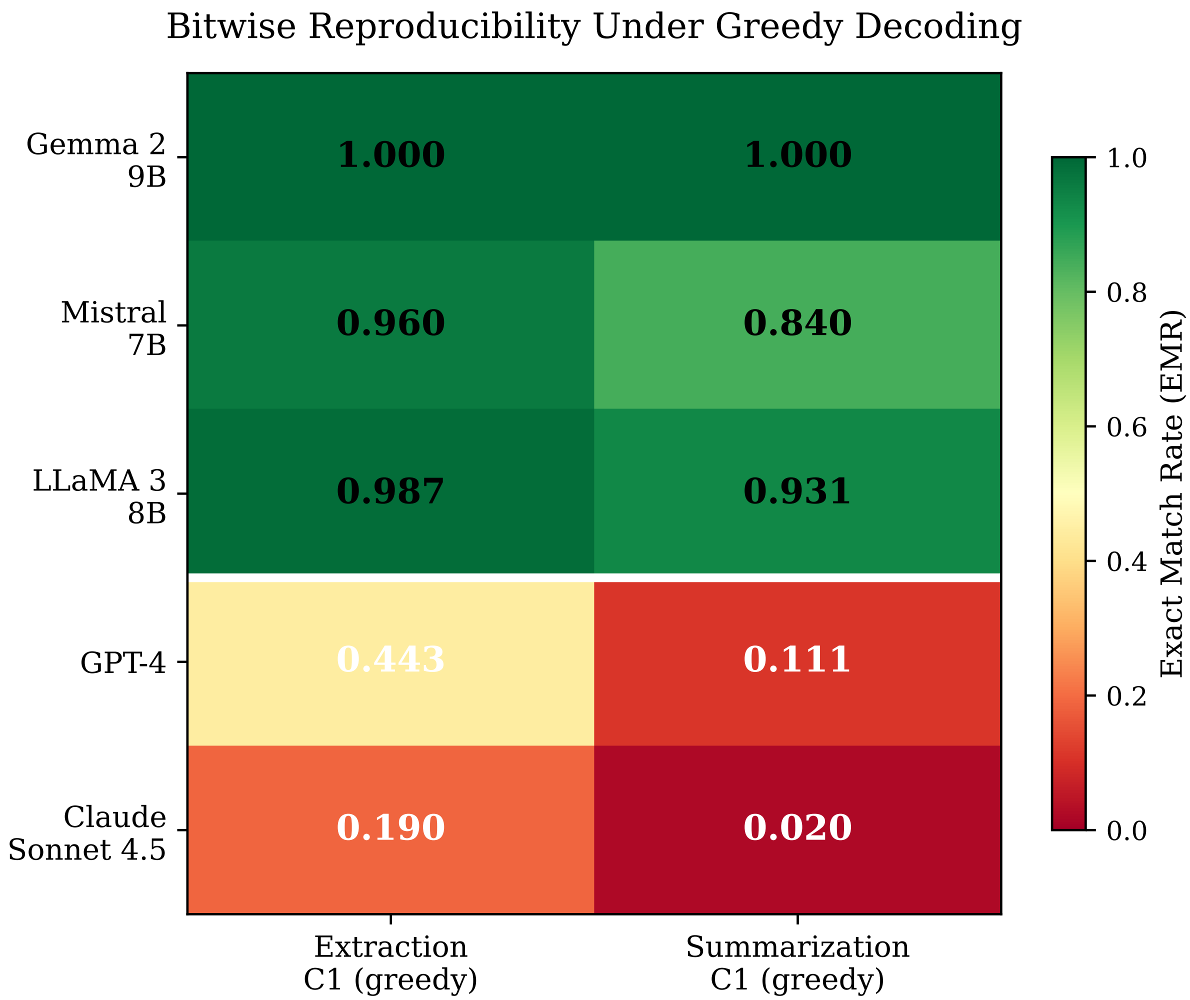

Fig. 3. Heatmap of Exact Match Rate under greedy decoding for five models. The horizontal white line separates local models (top three, green) from API-served models (bottom two, red). Gemma 2 9B achieves perfect 1.000 across all tasks.

overhead is consistent across local and API deployment modes, confirming that the protocol is deployment-agnostic.

Figure 5 provides an additional perspective on surface-level variability across models.

6 Discussion

The preceding results paint a clear and consistent picture across five models and four tasks: locally deployed models under greedy decoding achieve near-perfect to perfect bitwise reproducibility, while API-served models—from two independent providers—exhibit substantial hidden variability that researchers cannot control. Temperature is the dominant user-controllable factor, structured tasks are more reproducible than open-ended ones, and complex interaction regimes (multi-turn, RAG) do not degrade local-model reproducibility. We now consider what these

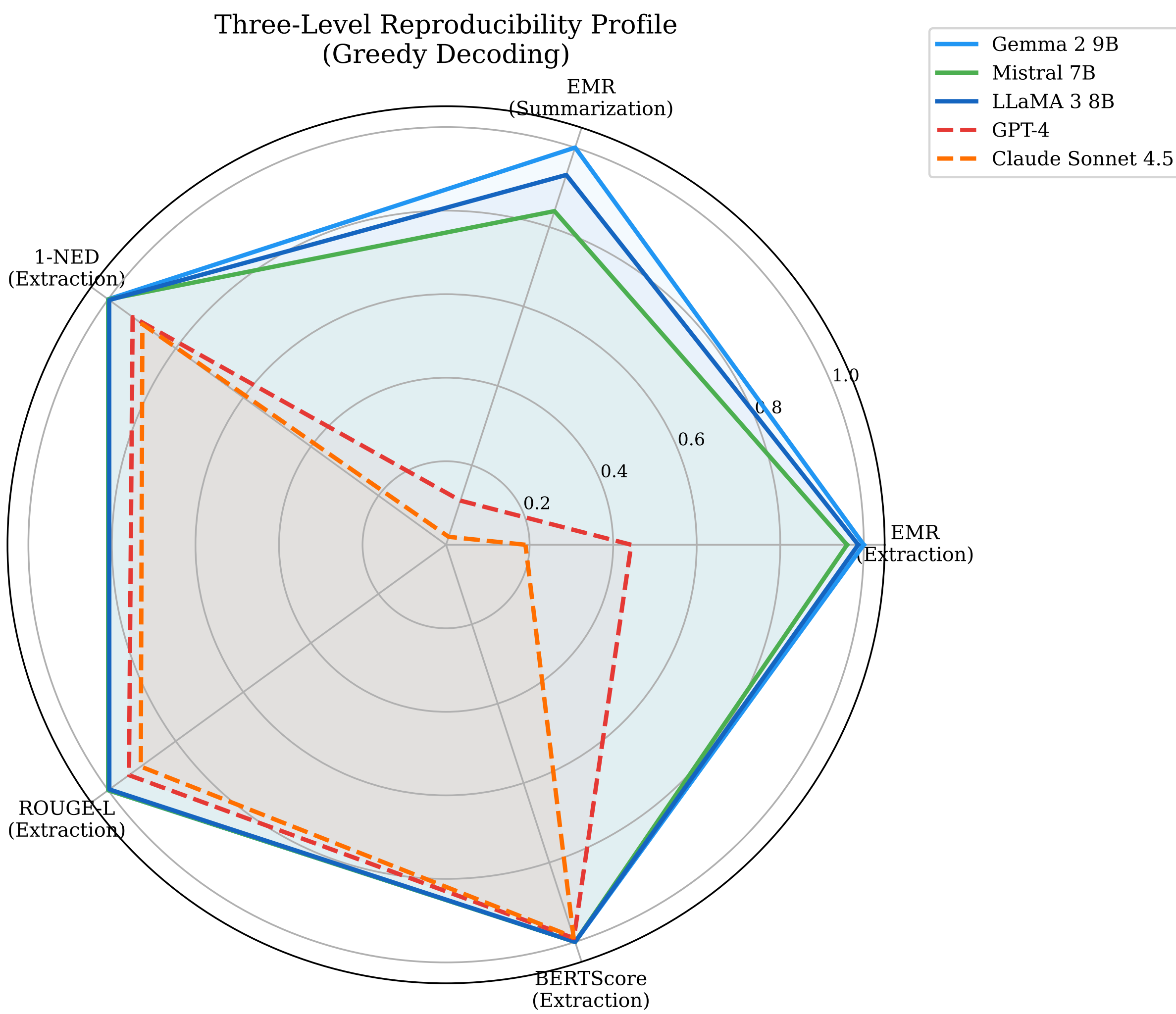

Fig. 4. Three-level reproducibility profiles under greedy decoding. Local models (solid lines) occupy the outer region across all five metrics, while API models (dashed lines) show pronounced deficits in EMR and NED while maintaining high BERTScore, indicating that API non-determinism is primarily lexical rather than semantic.

findings mean for research practice, what the protocol enables that was previously invisible, and where the current study's limitations lie.

6.1 Implications for Reproducibility Practice

Our results yield several actionable recommendations for researchers conducting generative AI experiments:

Use greedy decoding with local models for maximum reproducibility. Gemma 2 9B achieved *perfect* EMR = 1.000 across all tasks under greedy decoding. LLaMA 3 and Mistral 7B achieved EMR ≥ 0.840. Local deployment with t=0 should be the default configuration for any study in which output consistency is critical.

Table 9. Provenance logging overhead across five models under greedy decoding (C1). The protocol adds negligible overhead (<1%) to inference latency across all models and deployment modes.

Model	Source	Mean Inference (ms)	Mean Overhead (ms)	Overhead (%)
Gemma 2 9B	Local	181,579.3	30.6	0.234
Mistral 7B	Local	13,931.3	27.3	0.281
LLaMA 3 8B	Local	7,524.8	26.7	0.456
GPT-4	API	4,519.7	24.5	0.564
Claude Sonnet 4.5	API	4,359.3	26.5	0.727

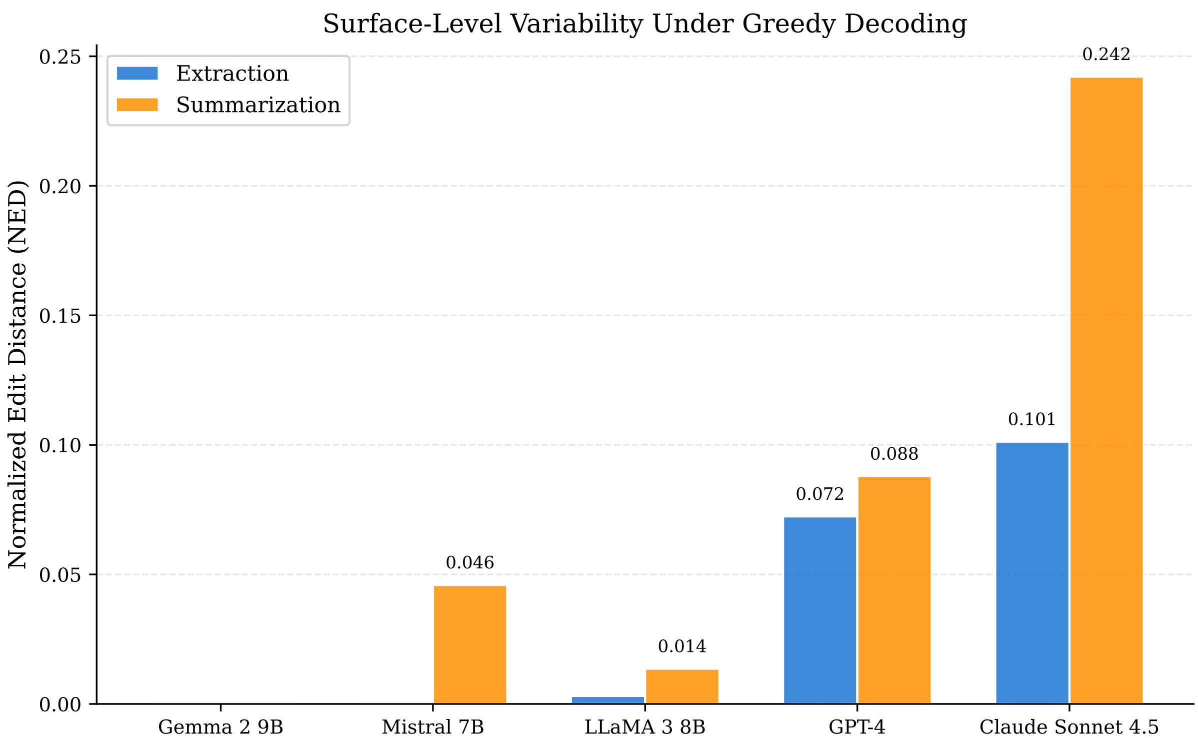

Fig. 5. Normalized Edit Distance (NED) under greedy decoding. Local models show near-zero NED (Gemma 2: 0.000, Mistral: 0.001), while API models exhibit NED 0.07–0.30, quantifying the surface-level divergence that accompanies the EMR gap.

API non-determinism is systemic, not provider-specific. Our most consequential finding is that *both* GPT-4 (OpenAI) and Claude Sonnet 4.5 (Anthropic) exhibit substantial non-determinism under greedy decoding. Claude's EMR of 0.020 for summarization means that effectively no two runs produce the same output. Researchers using *any* API-served model should never assume reproducibility without verification and should report multiple runs with variability metrics.

Prefer structured output formats when possible. The extraction task's consistently higher reproducibility across all five models demonstrates that output-format constraints directly improve reproducibility. This effect holds for both local models (EMR 0.960–1.000 for extraction vs. 0.840–1.000 for summarization) and API models (EMR 0.190–0.443 for extraction vs. 0.020–0.230 for summarization).

Include warm-up runs for local models. The per-abstract analysis revealed that the first inference call after model loading may differ from subsequent calls due to cache initialization. This affects LLaMA 3 and Mistral 7B on 2–4 of their abstracts, slightly reducing aggregate EMR.

Log comprehensively; the cost is negligible. At less than 1% overhead and approximately 4 KB per run across all five models, there is no practical reason not to apply comprehensive logging. The cost of not logging—namely, the inability to detect the kind of systemic API non-determinism documented herein—far exceeds the protocol's minimal requirements.

6.2 Local vs. API Inference: A Systemic Reproducibility Gap

The most significant finding of this study is the *systemic* reproducibility gap between local and API-based inference, now confirmed across two independent cloud providers. Under greedy decoding, local models average EMR = 0.960 while API models average EMR = 0.158—a 6× gap. The fact that Claude Sonnet 4.5 (Anthropic) exhibits *even lower* reproducibility than GPT-4 (OpenAI) rules out provider-specific implementation details as the sole explanation and points to fundamental properties of distributed cloud inference infrastructure.

This gap has profound implications for the scientific use of API-based LLMs. *Without systematic logging, a researcher using GPT-4 or Claude would have no way of knowing that their "deterministic" experiment produces different outputs across runs.* Our protocol makes this hidden non-determinism visible, measurable, and documentable.

6.3 Task-Dependent Reproducibility

The difference between summarization and extraction reproducibility—observed consistently across all five models—confirms and extends our earlier two-model finding. The reproducibility hierarchy (extraction > summarization) holds for local models (EMR gap of 0.03–0.12) and is amplified for API models (EMR gap of 0.17–0.25). This finding suggests a spectrum ranging from highly constrained tasks (structured extraction) to open-ended tasks (summarization), with the degree of output-space constraint serving as a primary determinant.

6.4 Multi-Turn and RAG: Reproducibility Under Complexity

Our multi-turn and RAG results address a key limitation of prior work (including our own earlier two-model study): reproducibility under complex interaction regimes. The finding that Gemma 2 9B and Mistral 7B maintain perfect EMR = 1.000 for both multi-turn refinement and RAG extraction demonstrates that conversational state accumulation and context augmentation do not inherently degrade reproducibility. LLaMA 3's slight degradation (EMR = 0.880 for multi-turn) suggests model-specific sensitivity to dialogue-turn interactions, possibly related to the warm-up effect observed in single-turn experiments.

6.5 The Role of Provenance

The W3C PROV graphs generated by our protocol serve multiple purposes beyond simple audit trails:

1. **Automated comparison**: By comparing PROV graphs of two runs, one can automatically identify which factors differed (e.g., same prompt and model but different temperatures), enabling systematic diagnosis of non-reproducibility.
2. **Lineage tracking**: When outputs are used as inputs to downstream processes (e.g., summarization outputs fed into a meta-analysis), the provenance chain can be extended to trace any final result back to its full generation context.
3. **Compliance**: For regulated domains (healthcare, legal, finance), PROV documents provide the formal evidence trail required by audit standards (National Institute of Standards and Technology 2023) and

emerging regulations such as the EU AI Act (European Parliament and Council of the European Union 2024).

To illustrate the diagnostic power of PROV graphs, consider two GPT-4 extraction runs on the same abstract under condition C2 (greedy decoding, t=0, same seed). Although the PROV entities for Prompt, InputText, ModelVersion, and InferenceParameters are identical (verified via matching SHA-256 hashes), the Output entities differ: `output_hash` values diverge, and the `wasGeneratedBy` timestamps differ by several seconds. The PROV graph thus automatically pinpoints the source of non-reproducibility: the only varying factor is the RunGeneration activity itself, consistent with non-determinism arising from server-side factors. This kind of automated differential diagnosis is infeasible without structured provenance records.

6.6 Limitations

We organize threats to validity following standard categories:

6.6.1 Internal Validity. **Sample size.** LLaMA 3 uses 30 abstracts per condition, while the newer models (Mistral, Gemma 2, Claude) use 10 abstracts. With $n = 30$, statistical power exceeds 0.999 for all primary comparisons (Cohen 1988). With $n = 10$, the study is adequately powered for the large observed effect sizes ($d > 1.6$) but may miss subtler effects.

GPT-4 C3 incomplete coverage. Due to API quota exhaustion, GPT-4 extraction under C3 conditions covers 14–17 of 30 abstracts (summarization C3 is complete at 30). Our central claims rest on the C2 condition (300/300 runs complete), and the C3 temperature sweep serves as a secondary analysis.

Warm-up confound. The first inference after model loading may differ from subsequent calls for LLaMA 3 and Mistral 7B. This affects 2–4 abstracts per model, slightly reducing aggregate EMR. Gemma 2 9B appears immune to this effect.

Prompt format confound. Single-turn experiments use Ollama's `/api/generate` endpoint for local models, whereas API models use their respective chat APIs. A supplementary control experiment (Appendix E) confirms that this format difference does not explain the reproducibility gap.

6.6.2 External Validity. **Five models, two paradigms.** Our evaluation now covers three local models and two API-served models, substantially strengthening the generalizability of the local-vs-API finding compared to single-model-per-paradigm designs. However, other models—including Gemini (Gemini Team et al. 2024), larger LLaMA variants, and open-weight models served via cloud APIs—may exhibit different characteristics.

Four tasks. Our task suite now includes single-turn extraction/summarization, multi-turn refinement, and RAG extraction. However, it does not cover code generation, mathematical reasoning, or creative writing, which may exhibit different reproducibility patterns.

English-only, single domain. Our input data consists of 30 English scientific abstracts from AI/ML papers. Reproducibility characteristics may differ for other languages, domains, or document types.

Multi-turn limited to local models. Multi-turn and RAG experiments were conducted only for the three local models. API-served models may exhibit different multi-turn reproducibility patterns.

6.6.3 Construct Validity. **Surface-level metrics.** Our metrics (EMR, NED, ROUGE-L) capture textual rather than semantic similarity. Two outputs that are semantically equivalent but syntactically different will register as non-matching under EMR and partially divergent under NED. This is by design—our focus is on *exact* reproducibility—but it means our results may overstate the practical impact of non-determinism for downstream applications where semantic equivalence suffices.

6.6.4 *Other Considerations.*

Privacy. The protocol's environment metadata includes the machine hostname, which may reveal institutional information. Deployments in privacy-sensitive settings should anonymize this field.

Computational cost. The total cost was modest: approximately 8 GPU-hours on a consumer laptop (Apple M4, 24 GB) for 2,000 local-model runs (including multi-turn and RAG experiments), plus 1,104 API calls to GPT-4 and Claude. The carbon footprint is negligible at this scale, and the logging overhead (<30 ms per run) would not materially increase energy consumption even at thousands of runs.

6.7 Protocol Minimality: An Ablation Analysis

To substantiate our claim that the protocol captures a *minimal* set of metadata, we conducted an ablation analysis in which we systematically removed each field group from the protocol schema and assessed which audit questions became unanswerable. We defined 10 audit questions that a reproducibility-oriented researcher might ask (e.g., "Can we verify the exact prompt used?", "Can we detect output tampering?", "Can we trace full provenance?") and mapped each to the protocol fields required to answer it. For this analysis, we decomposed the Run Card's five sections into eight finer-grained field groups by separating cross-cutting concerns: Identification, Model Context, Parameters, Input Content, Output Content, Hashing (all SHA-256 digests), Environment, and Overhead (timing and storage metadata).

The results show that removing *any* of these eight field groups renders at least one audit question unanswerable, confirming that no group is redundant. The Hashing group (SHA-256 hashes for prompts, inputs, outputs, parameters, and environment) has the highest information density: its removal affects 6 of 10 questions despite contributing only 410 bytes per run. Conversely, the Overhead group (logging time metadata) is the least connected but remains necessary for overhead assessment. The complete ablation results are available in the project repository.

This analysis demonstrates that the protocol is *minimal* in the sense that every field group is necessary for at least one audit capability, while the total overhead remains at approximately 4,052 bytes per run.

6.8 Practical Costs and Adoption

One concern with any new protocol is whether the adoption burden is justified. We address this concretely:

- **Implementation effort**: Our reference implementation adds approximately 600 lines of Python (the protocol core) to an existing workflow. Integration requires 3–5 function calls per run.
- **Runtime cost**: <30 ms per run across all five models, negligible compared to inference times of seconds to minutes for typical LLM calls.
- **Storage cost**: ~4 KB per run. Our 3,504 runs total approximately 14 MB—less than a single model checkpoint.
- **Learning curve**: The protocol uses standard JSON and W3C PROV, requiring no specialized knowledge beyond basic Python.

Against these modest costs, the protocol provides complete audit trails, automated provenance graphs, tamper-detectable outputs via cryptographic hashing, and structured metadata that enable systematic reproducibility analysis.

7 Conclusion

We presented a lightweight protocol for logging, versioning, and provenance tracking of generative AI experiments, introducing Prompt Cards and Run Cards as novel documentation artifacts and adopting the W3C PROV data model for machine-readable provenance graphs. Through 3,504 controlled experiments with five models—three locally deployed (LLaMA 3 8B, Mistral 7B, Gemma 2 9B) and two API-served (GPT-4, Claude Sonnet 4.5)—across four NLP tasks and 30 scientific abstracts, we demonstrated five key findings:

(1) **Server-side non-determinism is systemic, not provider-specific.** Both GPT-4 (OpenAI) and Claude Sonnet 4.5 (Anthropic) exhibit substantial non-determinism under greedy decoding (average EMR = 0.158), while all three local models achieve average EMR = 0.960. This 6× reproducibility gap is confirmed across two independent cloud providers, establishing API non-determinism as a fundamental property of distributed inference infrastructure.
(2) **Local models can achieve perfect bitwise reproducibility.** Gemma 2 9B attains EMR = 1.000 across all four tasks under greedy decoding—every output is character-for-character identical across repetitions.
(3) **Complex interaction regimes maintain reproducibility for local models.** Multi-turn refinement and RAG extraction achieve EMR ≥ 0.880 for all local models, with Gemma 2 9B and Mistral 7B maintaining perfect EMR = 1.000.
(4) **Temperature is the dominant user-controllable factor.** Increasing from t=0.0 to t=0.7 reduces EMR to zero for all five models on summarization, while seed variation has no effect under greedy decoding for local models.
(5) **Comprehensive provenance logging adds negligible overhead**: less than 1% of inference time and approximately 4 KB per run across all five models, removing any practical argument against systematic documentation.

These findings carry a broader implication: a substantial portion of published research that relies on API-based LLMs may contain non-reproducible results without the authors' knowledge. The cost of systematic provenance logging—less than one percent of inference time—is trivially small compared to the cost of publishing non-reproducible science.

Looking ahead, we plan to (i) extend the model suite to include Gemini (Gemini Team et al. 2024) and open-weight models served via cloud APIs (e.g., Hugging Face Inference Endpoints) to further disentangle model architecture from deployment infrastructure; (ii) extend the task coverage to code generation, mathematical reasoning, and agentic workflows; and (iii) develop automated reproducibility scoring based on provenance graph analysis. Ultimately, we envision a future in which every generative AI output carries a provenance certificate, and reproducibility metrics are reported alongside accuracy as a standard component of empirical evaluation.

The reference implementation, all 3,504 run records, provenance documents, and analysis scripts are publicly available to support adoption and independent verification.

Acknowledgments

This work was supported by UTFPR – Universidade Tecnológica Federal do Paraná. The experiments were conducted using locally deployed open-weight models to ensure full reproducibility of the computational environment.

Data Availability Statement

The reference implementation, all 3,504 run records (JSON), PROV-JSON provenance documents, Run Cards, Prompt Cards, input data, analysis scripts, and generated figures are publicly available at:

https://github.com/Roverlucas/genai-reproducibility-protocol

The repository includes instructions for reproducing all experiments and regenerating all tables and figures from the raw data.

Author Contributions

Following the CRediT (Contributor Roles Taxonomy) framework: **Lucas Rover**: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration. **Yara de Souza Tadano**: Supervision, Conceptualization, Methodology, Writing – Review & Editing, Project Administration.

Conflict of Interest

The authors declare no conflicts of interest. This research was conducted independently at UTFPR with no external funding from commercial AI providers. The use of OpenAI's GPT-4 API was for research evaluation purposes only and does not constitute an endorsement.

Use of AI-Assisted Tools

The authors used AI-assisted tools (Claude, Anthropic) during the preparation of this manuscript for language editing, code development support, and data analysis scripting. All AI-generated content was critically reviewed, validated, and revised by the authors, who take full responsibility for the accuracy and integrity of the final manuscript. The scientific design, experimental execution, interpretation of results, and intellectual contributions are entirely the authors' own work.

References

J. Achiam et al.. 2023. *GPT-4 Technical Report*. arXiv preprint. (2023). arXiv: 2303.08774 (cs.CL).

Anthropic. 2024. *The Claude Model Family*. (2024). https://www.anthropic.com/claude.

B. Atil et al.. 2024. *Non-Determinism of "Deterministic" LLM Settings*. arXiv preprint. (2024). arXiv: 2408.04667 (cs.CL).

M. Baker. 2016. "1,500 Scientists Lift the Lid on Reproducibility." *Nature*, 533, 7604, 452–454. doi:10.1038/533452a.

A. Belz, S. Agarwal, A. Shimorina, and E. Reiter. 2021. "A Systematic Review of Reproducibility Research in Natural Language Processing." In: *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 381–393. doi:10.18653/v1/2021.eacl-main.29.

L. Biewald. 2020. *Experiment Tracking with Weights and Biases*. (2020). https://wandb.com/.

R. Bommasani et al.. 2022. *On the Opportunities and Risks of Foundation Models*. arXiv preprint. (2022). arXiv: 2108.07258 (cs.LG).

T. Brown et al.. 2020. "Language Models are Few-Shot Learners." In: *Advances in Neural Information Processing Systems*. Vol. 33, 1877–1901. arXiv: 2005.14165 (cs.CL).

Y. Chen, J. Li, X. Liu, and Y. Li. 2023. *On the Reproducibility of ChatGPT in NLP Tasks*. arXiv preprint. (2023). arXiv: 2304.02554 (cs.CL).

J. Cohen. 1988. *Statistical Power Analysis for the Behavioral Sciences*. (2nd ed.). Lawrence Erlbaum Associates. ISBN: 978-0-8058-0283-2.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. 2019. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 4171–4186. doi:10.18653/v1/N19-1423.

J. Dodge, S. Gururangan, D. Card, R. Schwartz, and N. A. Smith. 2019. "Show Your Work: Improved Reporting of Experimental Results." In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2185–2194. doi:10.18653/v1/D19-1224.

European Parliament and Council of the European Union. 2024. *Regulation (EU) 2024/1689 Laying Down Harmonised Rules on Artificial Intelligence (AI Act)*. (2024). https://eur-lex.europa.eu/eli/reg/2024/1689/oj.

T. Gebru, J. Morgenstern, B. Vecchione, J. W. Vaughan, H. Wallach, H. Daumé III, and K. Crawford. 2021. "Datasheets for Datasets." *Communications of the ACM*, 64, 12, 86–92. doi:10.1145/3458723.

Gemini Team, R. Anil, S. Borgeaud, J.-B. Alayrac, J. Yu, R. Soricut, J. Schalkwyk, A. M. Dai, A. Hauth, et al.. 2024. *Gemini: A Family of Highly Capable Multimodal Models*. arXiv preprint. (2024). arXiv: 2312.11805 (cs.CL).

Gemma Team et al.. 2024. *Gemma 2: Improving Open Language Models at a Practical Size*. arXiv preprint. (2024). arXiv: 2408.00118 (cs.CL).

A. Grattafiori, A. Dubey, A. Jauhri, A. Pandey, A. Kadian, A. Al-Dahle, A. Letman, A. Mathur, A. Schelten, et al.. 2024. *The LLaMA 3 Herd of Models*. arXiv preprint. (2024). arXiv: 2407.21783 (cs.AI).

O. E. Gundersen, Y. Gil, and D. W. Aha. 2018. "On Reproducible AI: Towards Reproducible Research, Open Science, and Digital Scholarship in AI Publications." *AI Magazine*, 39, 3, 56–68. doi:10.1609/aimag.v39i3.2816.

O. E. Gundersen, M. Helmert, and H. H. Hoos. 2024. "Improving Reproducibility in AI Research: Four Mechanisms Adopted by JAIR." *Journal of Artificial Intelligence Research*, 81, 1019–1041. doi:10.1613/jair.1.16905.

O. E. Gundersen and S. Kjensmo. 2018. "State of the Art: Reproducibility in Artificial Intelligence." *Proceedings of the AAAI Conference on Artificial Intelligence*, 32, 1, 1644–1651. doi:10.1609/aaai.v32i1.11503.

M. Herschel, R. Diestelkämper, and H. Ben Lahmar. 2017. "A Survey on Provenance: What for? What form? What from?" *The VLDB Journal*, 26, 6, 881–906. doi:10.1007/s00778-017-0486-1.

M. Hutson. 2018. "Artificial Intelligence Faces Reproducibility Crisis." *Science*, 359, 6377, 725–726. doi:10.1126/science.359.6377.725.

A. Q. Jiang et al.. 2023. *Mistral 7B*. arXiv preprint. (2023). arXiv: 2310.06825 (cs.CL).

S. Kapoor and A. Narayanan. 2023. "Leakage and the Reproducibility Crisis in Machine-Learning-Based Science." *Patterns*, 4, 9, 100804. doi:10.1016/j.patter.2023.100804.

R. Kuprieiev, D. Petrov, and Iterative. 2024. *DVC: Data Version Control*. (2024). https://dvc.org/.

LangChain. 2023. *LangSmith: A Platform for Building Production-Grade LLM Applications*. (2023). https://smith.langchain.com/.

V. I. Levenshtein. 1966. "Binary Codes Capable of Correcting Deletions, Insertions, and Reversals." *Soviet Physics Doklady*, 10, 8, 707–710.

P. Liang et al.. 2023. "Holistic Evaluation of Language Models." *Transactions on Machine Learning Research*. https://openreview.net/forum?id=iO4LZibEqW.

C.-Y. Lin. 2004. "ROUGE: A Package for Automatic Evaluation of Summaries." In: *Proceedings of the ACL-04 Workshop on Text Summarization Branches Out*. Association for Computational Linguistics, 74–81. https://aclanthology.org/W04-1013/.

M. Mitchell, S. Wu, A. Zaldivar, P. Barnes, L. Vasserman, B. Hutchinson, E. Spitzer, I. D. Raji, and T. Gebru. 2019. "Model Cards for Model Reporting." In: *Proceedings of the Conference on Fairness, Accountability, and Transparency*. ACM, 220–229. doi:10.1145/3287560.3287596.

L. Moreau and P. Missier. 2013. *PROV-DM: The PROV Data Model*. W3C Recommendation. World Wide Web Consortium. https://www.w3.org/TR/prov-dm/.

National Institute of Standards and Technology. 2023. *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. Tech. rep. U.S. Department of Commerce. doi:10.6028/NIST.AI.100-1.

Ollama. 2024. *Ollama: Run Large Language Models Locally*. (2024). https://ollama.com/.

OpenAI. 2023. *OpenAI Evals: A Framework for Evaluating LLMs*. (2023). https://github.com/openai/evals.

S. Ouyang, J. M. Zhang, M. Harman, and M. Wang. 2024. "An Empirical Study of the Non-determinism of ChatGPT in Code Generation." *ACM Transactions on Software Engineering and Methodology*, 34, 2, 1–28. doi:10.1145/3697010.

G. Padovani, V. Anantharaj, and S. Fiore. 2025. "yProv4ML: Effortless Provenance Tracking for Machine Learning Systems." *SoftwareX*, 29, 102028. doi:10.1016/j.softx.2025.102028.

J. Pineau, P. Vincent-Lamarre, K. Sinha, V. Larivière, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and H. Larochelle. 2021. "Improving Reproducibility in Machine Learning Research: A Report from the NeurIPS 2019 Reproducibility Program." *Journal of Machine Learning Research*, 22, 164, 1–20. https://jmlr.org/papers/v22/20-303.html.

C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu. 2020. "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer." *Journal of Machine Learning Research*, 21, 140, 1–67. https://jmlr.org/papers/v21/20-074.html.

S. Samuel and B. König-Ries. 2022. "A Provenance-based Semantic Approach to Support Understandability, Reproducibility, and Reuse of Scientific Experiments." *Journal of Biomedical Semantics*, 13, 1, 1–30. doi:10.1186/s13326-022-00263-z.

V. Stodden, M. McNutt, D. H. Bailey, E. Deelman, Y. Gil, B. Hanson, M. A. Heroux, J. P. Ioannidis, and M. Taufer. 2016. "Enhancing Reproducibility for Computational Methods." *Science*, 354, 6317, 1240–1241. doi:10.1126/science.aah6168.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. 2017. "Attention is All You Need." In: *Advances in Neural Information Processing Systems*. Vol. 30. Curran Associates, Inc. arXiv: 1706.03762 (cs.CL).

J. Wei, X. Wang, D. Schuurmans, M. Bosma, B. Ichter, F. Xia, E. H. Chi, Q. V. Le, and D. Zhou. 2022. "Chain-of-Thought Prompting Elicits Reasoning in Large Language Models." In: *Advances in Neural Information Processing Systems*. Vol. 35, 24824–24837. arXiv: 2201.11903 (cs.CL).

M. D. Wilkinson et al.. 2016. "The FAIR Guiding Principles for Scientific Data Management and Stewardship." *Scientific Data*, 3, 160018. doi:10.1038/sdata.2016.18.

J. Yuan et al.. 2025. "Understanding and Mitigating Numerical Sources of Nondeterminism in LLM Inference." In: *Advances in Neural Information Processing Systems*. Vol. 38. arXiv preprint. Curran Associates, Inc. arXiv: 2506.09501 (cs.LG).

M. Zaharia et al.. 2018. "Accelerating the Machine Learning Lifecycle with MLflow." *IEEE Data Engineering Bulletin*, 41, 4, 39–45. http://sites.computer.org/debull/A18dec/p39.pdf.

T. Zhang, V. Kishore, F. Wu, K. Q. Weinberger, and Y. Artzi. 2020. "BERTScore: Evaluating Text Generation with BERT." In: *Proceedings of the 8th International Conference on Learning Representations*. https://openreview.net/forum?id=SkeHuCVFDr.

Y. Zhu, P. Zhang, E. Haq, P. Hui, and G. Buchanan. 2023. *Can ChatGPT Reproduce Human-Generated Labels? A Study of Social Computing Tasks*. arXiv preprint. (2023). arXiv: 2304.10145 (cs.CL).

A Reproducibility Checklist

The following checklist is designed for self-assessment of reproducibility in generative AI studies. Each item maps to a specific field or artifact in our protocol.

Prompt Documentation

(1) Is the exact prompt text recorded and versioned? [Prompt Card: `prompt_text`, `prompt_hash`]
(2) Are design assumptions and limitations documented? [Prompt Card: `assumptions`, `limitations`]
(3) Is the expected output format specified? [Prompt Card: `expected_output_format`]
(4) Is the interaction regime documented (single/multi-turn)? [Prompt Card: `interaction_regime`]

Model and Environment

(5) Is the model name and version recorded? [Run Card: `model_name`, `model_version`]
(6) Are model weights hashed for identity verification? [Run Card: `weights_hash`]
(7) Is the execution environment fingerprinted? [Run Card: `environment`, `environment_hash`]
(8) Is the source code version recorded? [Run Card: `code_commit`]

Execution and Output

(9) Are all inference parameters logged? [Run Card: `inference_params`]
(10) Is the random seed recorded? [Run Card: `inference_params.seed`]
(11) Is the output cryptographically hashed? [Run Card: `output_hash`]
(12) Are execution timestamps recorded? [Run Card: `timestamp_start`, `timestamp_end`]
(13) Is logging overhead measured separately? [Run Card: `logging_overhead_ms`]

Provenance

(14) Is a provenance graph generated per group? [PROV-JSON document]
(15) Are provenance documents in an interoperable format? [W3C PROV standard]

B Run Card Schema

The complete Run Card schema, with data types and descriptions:

Listing 1. Run Card JSON schema (simplified).

```
{
  "run_id": "string (unique identifier)",
  "task_id": "string (task identifier)",
  "task_category": "string (e.g., summarization)",
  "prompt_hash": "string (SHA-256 of prompt)",
  "prompt_text": "string (full prompt text)",
  "input_text": "string (input to the model)",
  "input_hash": "string (SHA-256 of input)",
  "model_name": "string (e.g., llama3:8b)",
  "model_version": "string (e.g., 8.0B)",
  "weights_hash": "string (SHA-256 of weights)",
  "model_source": "string (e.g., ollama-local)",
  "inference_params": {
    "temperature": "float",
    "top_p": "float",
```

```
    "top_k": "integer",
    "max_tokens": "integer",
    "seed": "integer|null",
    "decoding_strategy": "string"
  },
  "params_hash": "string (SHA-256 of params)",
  "environment": {
    "os": "string",
    "os_version": "string",
    "architecture": "string",
    "python_version": "string",
    "hostname": "string",
    "timestamp": "ISO 8601 datetime"
  },
  "environment_hash": "string (SHA-256)",
  "code_commit": "string (git commit hash)",
  "researcher_id": "string",
  "affiliation": "string",
  "timestamp_start": "ISO 8601 datetime",
  "timestamp_end": "ISO 8601 datetime",
  "output_text": "string (model output)",
  "output_hash": "string (SHA-256 of output)",
  "output_metrics": "object (task-specific)",
  "execution_duration_ms": "float",
  "logging_overhead_ms": "float",
  "storage_kb": "float",
  "system_logs": "string (raw system info)",
  "errors": "array of strings"
}
```

C Example PROV-JSON Document

An abbreviated example of a PROV-JSON document generated for a single summarization run:

Listing 2. Abbreviated PROV-JSON for a summarization run.


```
{
  "prefix": {
    "genai": "https://genai-prov.org/ns#",
    "prov": "http://www.w3.org/ns/prov#"
  },
  "entity": {
    "genai:prompt_c9644358": {
      "prov:type": "genai:Prompt",
      "genai:hash": "c9644358805b...",
      "genai:task_category": "summarization"
    },
    "genai:model_llama3_8b": {
      "prov:type": "genai:ModelVersion",
      "genai:name": "llama3:8b",
      "genai:source": "ollama-local"
```

```
    },
    "genai:output_590d0835": {
      "prov:type": "genai:Output",
      "genai:hash": "590d08359e7d..."
    }
  },
  "activity": {
    "genai:run_llama3_8b_sum_001_C1_rep0": {
      "prov:type": "genai:RunGeneration",
      "prov:startTime": "2026-02-07T21:54:34Z",
      "prov:endTime": "2026-02-07T21:54:40Z"
    }
  },
  "wasGeneratedBy": {
    "_:wGB1": {
      "prov:entity": "genai:output_590d0835",
      "prov:activity": "genai:run_llama3_8b_..."
    }
  },
  "used": {
    "_:u1": {
      "prov:activity": "genai:run_llama3_...",
      "prov:entity": "genai:prompt_c9644358"
    }
  },
  "agent": {
    "genai:researcher_lucas_rover": {
      "prov:type": "prov:Person",
      "genai:affiliation": "UTFPR"
    }
  },
  "wasAssociatedWith": {
    "_:wAW1": {
      "prov:activity": "genai:run_llama3_...",
      "prov:agent": "genai:researcher_..."
    }
  }
}
```

D JSON Extraction Quality

Table 10 presents JSON-specific quality metrics for the structured extraction task. Two notable patterns emerge.

First, LLaMA 3 never produces raw-valid JSON: all 570 extraction outputs contain preamble text (e.g., "Here is the extracted information in JSON format:") before the JSON object, despite the prompt explicitly requesting "JSON only, no explanation." After extracting the embedded JSON via regex, validity rates reach 100% under greedy decoding, degrading slightly at higher temperatures (92.2% at t=0.7). GPT-4, by contrast, always produces raw-valid JSON with 100% schema compliance across all conditions. This instruction-following gap is consistent with the different prompt interfaces: the chat completion API's structured message format may better signal the expected output format.

Table 10. JSON extraction quality metrics by model and condition. *Raw Valid* = output parses directly as JSON; *Extracted Valid* = JSON extracted via regex from outputs containing preamble text; *Schema* = all five expected fields present; *Field EMR* = within-abstract pairwise exact match across runs for each extracted field, averaged over abstracts (see Section D for interpretation). LLaMA 3 always prepends introductory text (e.g., "Here is the extracted information in JSON format:"), yielding 0% raw validity but near-perfect extracted validity at t=0.

Model	Cond.	Raw Valid	Extr. Valid	Schema Compl.	Within-Abstract Field EMR					Overall Field EMR
					obj	meth	key_r	mod/sys	bench	
LLaMA 3	C1 (t=0)	0%	100%	100%	0.987	0.987	0.987	1.000	0.987	0.989
	C2 (t=0)	0%	100%	100%	0.987	0.987	0.987	1.000	0.987	0.989
	C3 (t=0.0)	0%	100%	100%	0.978	0.978	0.978	1.000	0.978	0.982
	C3 (t=0.3)	0%	97.8%	97.8%	0.747	0.460	0.552	0.862	0.805	0.685
	C3 (t=0.7)	0%	92.2%	92.2%	0.522	0.167	0.267	0.611	0.711	0.456
GPT-4	C2 (t=0)	100%	100%	100%	0.773	0.667	0.637	0.893	0.863	0.767
	C3 (t=0.0)	100%	100%	100%	0.833	0.571	0.667	0.905	0.810	0.757
	C3 (t=0.3)	100%	100%	100%	0.405	0.262	0.452	0.762	0.690	0.514
	C3 (t=0.7)	100%	100%	100%	0.137	0.157	0.255	0.667	0.725	0.388

Second, within-abstract field-level exact match rates—computed by comparing only runs of the *same* abstract under the same condition, then averaging across abstracts—confirm the overall reproducibility hierarchy. Under greedy decoding, LLaMA 3 achieves near-perfect field EMR (0.982–0.989 overall), with all five fields at or above 0.978, consistent with the overall extraction EMR of 0.987 reported in Table 4. GPT-4 under greedy shows lower field EMR (0.757–0.767 overall), with open-ended fields (`method`: 0.667, `key_result`: 0.637) lagging behind structured fields (`model_or_system`: 0.893, `benchmark`: 0.863). As temperature increases, this gap widens: at t=0.7, `method` drops to 0.167 (LLaMA) and 0.157 (GPT-4), while `benchmark` retains 0.711 and 0.725 respectively—a 4–5× difference. This within-abstract formulation isolates true reproducibility (same input, same conditions, different runs) from between-abstract content variation, providing a methodologically clean measure of field-level consistency.

E Chat-Format Control Experiment

To assess whether the prompt-format difference between LLaMA 3 (completion-style via `/api/generate`) and GPT-4 (chat-style via Chat Completions) contributes to the observed reproducibility gap, we conducted a supplementary control experiment running LLaMA 3 8B through Ollama's `/api/chat` endpoint, which applies the model's chat template (including special tokens for system/user/assistant roles) in the same message structure used by GPT-4.

Design: 10 abstracts × 2 tasks × 2 conditions (C1, C2) × 5 repetitions = 200 runs, all under greedy decoding (t=0).

Results: Table 11 compares the chat-format control with the original completion-format results for the same 10 abstracts. The two prompt formats produce *identical* variability metrics across all conditions: summarization EMR = 0.929, NED = 0.0066, and ROUGE-L = 0.9922 in both modes; extraction achieves perfect reproducibility (EMR = 1.000) regardless of interface. The 0.929 summarization EMR reflects the warm-up effect on 2 of 10 abstracts—the same pattern observed in the full 30-abstract experiment. These results confirm that prompt format is not a source of variability, and the reproducibility gap between LLaMA 3 and GPT-4 is consistent with deployment-side factors (server infrastructure, floating-point non-determinism across GPU types, request batching) rather than prompt-format differences.

Table 11. Prompt-format control: LLaMA 3 8B via completion (`/api/generate`) vs. chat (`/api/chat`) for 10 abstracts under greedy decoding (t=0). EMR computed over conditions C1 and C2 combined.

Task	**Metric**	**Completion**	**Chat**
Summarization	EMR↑	0.929	0.929
	NED↓	0.0066	0.0066
	ROUGE-L↑	0.9922	0.9922
Extraction	EMR↑	1.000	1.000
	NED↓	0.0000	0.0000
	ROUGE-L↑	1.0000	1.0000

Note: Completion and chat formats yield identical metrics for all 10 abstracts under greedy decoding, confirming prompt format is not a source of variability.

Received February 2026