

# Hallucination or Creativity: How to Evaluate AI-Generated Scientific Stories?

Alex Argese<sup>1</sup>, Pasquale Lisena<sup>1,\*</sup> and Raphaël Troncy<sup>1</sup>

<sup>1</sup>EURECOM, Sophia Antipolis, France

## Abstract

Generative AI can turn scientific articles into narratives for diverse audiences, but evaluating these stories remains challenging. Storytelling demands abstraction, simplification, and pedagogical creativity—qualities that are not often well-captured by standard summarization metrics. Meanwhile, factual hallucinations are critical in scientific contexts, yet, detectors often misclassify legitimate narrative reformulations or prove unstable when creativity is involved. In this work, we propose StoryScore, a composite metric for evaluating AI-generated scientific stories. StoryScore integrates semantic alignment, lexical grounding, narrative control, structural fidelity, redundancy avoidance, and entity-level hallucination detection into a unified framework. Our analysis also reveals why many hallucination detection methods fail to distinguish pedagogical creativity from factual errors, highlighting a key limitation: while automatic metrics can effectively assess semantic similarity with original content, they struggle to evaluate how it is narrated and controlled.

## Keywords

Scientific Storytelling, Generative AI, AI evaluation, LLM, Hallucination Detection

## 1. Introduction

Generative AI in general and Large language models (LLMs) in particular can summarize and rephrase complex content, presenting it in a narrative form that makes it accessible to non-experts [1]. Despite these advances, LLMs frequently struggle to appropriately adapt tone, level of detail, and stylistic choices to diverse audiences and communication objectives, regardless of the amount of contextual instructions and roles than one can use when prompting. In addition, LLMs are prone to hallucinations, eloquently stating unsupported claims, which pose a significant risk in scientific communication [2].

Recent works are exploring *scientific storytelling* as a way to generate structured and engaging narratives that explain scientific content and papers while tailoring explanations to specific personas [3, 4]. However, evaluating such narratives presents challenges that differ fundamentally from those associated with traditional summarization tasks. Persona-oriented storytelling deliberately introduces abstraction, metaphor, and contextualization to enhance accessibility. These transformations are desirable for communication but significantly complicate evaluation. In particular, assessing factual grounding becomes non-trivial when the generated text is not expected to closely mirror the source document.

While the development of scientific storytelling systems is gaining momentum, the question of how to evaluate the resulting narratives remains largely open. In particular:

- (RQ1) How can the quality of a scientific story be evaluated beyond surface-level similarity to the source paper, while accounting for narrative coherence and persona adaptation?
- (RQ2) How can hallucinations be reliably identified in stories where creative reformulation is not only expected but encouraged?
- (RQ3) To what extent do existing hallucination detection methods conflate legitimate abstraction with factual inconsistency in scientific storytelling?

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\*Corresponding author.

 alex.argese@eurecom.fr (A. Argese); pasquale.lisena@eurecom.fr (P. Lisena); raphael.troncy@eurecom.fr (R. Troncy)

 0009-0005-6151-5723 (A. Argese); 0000-0003-3094-5585 (P. Lisena); 0000-0003-0457-1436 (R. Troncy)



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In this work, we address these questions in the context of designing a system that transform scientific papers into audience-adapted stories. We make two main contributions:

1. *StoryScore*, a composite metric for automatic evaluation of scientific story generation;
2. an empirical analysis of hallucination detection methods in persona-adaptive storytelling, showing why many approaches conflate creativity with hallucination.

The remainder of the paper is organised as follows. After reviewing the relevant literature in Section 2, we introduce the background use case in Section 3. We detail the StoryScore metric in Section 4. Next, we discuss the limitations of existing hallucination detection methods for our use case in Section 5. We present the findings of our experiments in Section 6. Finally, we conclude and outline some future work in Section 7. The code<sup>1</sup> and data<sup>2</sup> used in this work are publicly available.

## 2. Related Work

**Narrative Storytelling in Science Communication.** Research shows that framing scientific content as a narrative significantly improves public comprehension, engagement [5] and recall of facts [6]. Scientific communication research emphasizes that effective dissemination requires deliberate choices about framing, analogy, structure, and level of detail, depending on the reader’s background and goals [7, 8]. Recent work has also explored persona-driven or audience-aware generation to adapt explanations, tone, and terminology to reader profiles, showing benefits for accessibility and engagement but raising new requirements for evaluation beyond factuality alone [3, 4].

In human-AI interaction settings, researchers are exploring tools to help scientists crafting such narratives. A recent example is *RevTogether* that describes a multi-agent AI system that helps writers to revise “science stories” by blending engaging narrative structure with clear scientific content [9].

**Automatic evaluation of generated narratives.** Evaluating the quality of AI-generated stories or summaries has also advanced beyond simple word-overlap scores. Traditional metrics like ROUGE [10] measure n-gram overlap with reference summaries, but they correlate poorly with human judgments [11, 12, 13]. Semantic metrics such as BERTScore [14] and MoverScore [15] use contextual embeddings to better capture semantic alignment and compare meaning rather than surface words. They achieve high correlation with human ratings on summarization and other tasks, but remain largely insensitive to structural degradation, redundancy, and discourse-level control failures, which are critical in storytelling. This gap is amplified in multi-section stories, where discourse-level issues (e.g., global coherence, redundancy, or instruction leakage) strongly affect perceived quality while remaining weakly captured by similarity-based metrics. Other methods, such as QuestEval [12] and QAGS [16] ask questions about a summary and its source to detect factual inconsistencies.

**Hallucination detection.** Hallucination detection has been studied extensively in summarization and question answering, using entity-based checks, retrieval and entailment methods, and LLM-based judges [17, 2, 18]. Systems can use RAG-based techniques on specific documents or on the web, like the widely adopted GPTZero<sup>3</sup>. Notably, recent empirical work shows pitfalls in automated detection. For example, they show that ROUGE and similar metrics can be easily fooled – e.g. repetitively duplicating correct content (adding length) artificially inflates ROUGE scores, even though no new facts are added [19]. In addition, common approaches often assume strict fidelity to the source. In persona-adaptive storytelling, legitimate reformulations and contextual expansions are expected. Thus, detectors can over-penalize creativity or behave unstably. We will critically analyse existing methods in Section 5.

<sup>1</sup><https://anonymous.4open.science/r/scientist-storyteller-2026>

<sup>2</sup><https://zenodo.org/records/18301594>

<sup>3</sup><https://gptzero.me/>

### 3. Use Case: An AI-Driven Pipeline for Scientific Story Generation

The metrics proposed in this paper are grounded in a concrete use case: generating persona-adapted explanatory stories from scientific papers. We employ a two-stage pipeline in which a *Splitter* module produces a five-section outline from a scientific paper, and a *Storyteller* module expands each section into a persona-conditioned narrative. In our implementation, the Splitter uses the Qwen2.5-7B [20] model for stable structured output, while the Storyteller relies on the Qwen2.5-32B model for long-context generation, persona adherence, and reduced hallucinations. Specific prompts constrain the output structure and discourage the invention of entities, numeric values, or references, while allowing simplification and contextualization.

We conducted experiments on a curated dataset of 62 scientific papers paired with 190 human-written explanatory stories across three domains (Entertainment, Accessibility, Health) and eight personas. From this corpus, we derive 496 outline instances for training the Splitter and 818 story-level instances (4,090 section texts) for training the Storyteller, using standard train/validation/test splits. The test set is used to generate persona-adapted stories that serve as evaluation material for StoryScore and for the comparative analysis of hallucination detection methods detailed below.

### 4. The StoryScore metric for Generated Story Evaluation

The evaluation of stories generated from research papers, and in general, generated from a source material, requires metrics that balance faithfulness, completeness, and narrative quality under conditions of intentional abstraction. An effective evaluation framework should ensure that a generated story (i) **maintains semantic fidelity and representativeness** with respect to the source work, capturing the key content accurately even under extensive paraphrasing or reorganization; (ii) **preserves textual integrity**, minimizing artifacts and avoiding hallucinations introduced during generation; and (iii) **achieves structural and communicative adequacy**, ensuring coherent organization, appropriate titling, and elimination of unnecessary repetition. These requirements call for an evaluation approach that integrates complementary signals rather than relying on a single notion of similarity or correctness.

For this reason, we propose **StoryScore**, a composite metric aggregating semantic similarity, lexical grounding, structural fidelity, fluency, and hallucination control into a single score in the range [0, 1]. Following extensive experimentation on a real use case, including a multi-stage analysis of hallucination detection explained later, it is defined as:

$$\text{StoryScore} = (0.3 \text{ ContextRecall}) + (0.2 \text{ BERTScore}) + (0.2 \text{ PromptCleanliness}) + (0.1 \text{ TitleCoverage}) + (0.1 \text{ NoRedundancy}) + (0.1 \text{ NoHallucination}) \quad (1)$$

This formulation captures the most stable and reliable indicators, maintaining a balanced representation of narrative quality dimensions. The weights were selected heuristically after exploratory adjustments guided by manual qualitative inspection, with the goal of producing an aggregate score consistent with human qualitative judgments. The components of *StoryScore* are summarised in Table 1.

**Context recall** or **Article coverage** quantifies the amount of content from the original article that is reflected in the generated story, measured as the proportion of word-level lexical tokens from the article that also appear in the narrative (article-centered coverage). Tokens are defined as lowercased words, excluding punctuation and stopwords. Unlike metrics that rely solely on lexical overlap, contextual recall serves as a proxy for content coverage, quantifying the extent to which the generated text captures the key concepts, terminology, and salient tokens from the original article. Formally, it is defined as:

$$\text{ContextRecall} = \frac{|T_{\text{story}} \cap T_{\text{paper}}|}{|T_{\text{paper}}|} \quad (2)$$

where  $T_{\text{paper}}$  and  $T_{\text{story}}$  denote the sets of tokens extracted from the paper and the generated story. Higher values indicate stronger grounding in the source material, but also a vocabulary that is more

Metric	Type	Objective
Context Recall	Lexical	Proportion of tokens from the original paper covered by the story
BERTScore	Semantic	Faithfulness of the story to the original content
Prompt Cleanliness	Structural	Absence of instruction leakage and prompt-related artifacts
Title Coverage	Structural	Similarity between generated and original section titles
NoRedundancy	Fluency	Avoidance of repeated $n$ -gram loops and redundant phrasing patterns
NoHallucination	Factuality	Entity consistency (PERSON/ORG as detected by SpaCy) with the paper
StoryScore	Composite	Global weighted quality score

**Table 1**

Summary of evaluation metrics used in this work. All components are in the  $[0, 1]$  range.

faithful to the vocabulary used in the paper and less persona-adapted for an audience with low expertise. We intentionally adopt a simple set-based formulation to obtain a transparent and stable signal, acknowledging that this choice favours lexical grounding over semantic abstraction and may penalize aggressive simplification.

**BERTScore** [14] measures **semantic faithfulness** by comparing contextual embeddings of the generated story with those of the source article. BERTScore aligns tokens from the hypothesis to the most semantically similar tokens in the reference using cosine similarity in the embedding space. For each token, the F1-score are computed by aggregating the highest-scoring matches. Formally, let  $H$  and  $R$  be the embedding sets for the hypothesis (story) and reference (paper), BERTScore is defined as:

$$\text{BERTScore} = F_1(\text{sim}(H, R), \text{sim}(R, H)) \quad (3)$$

where  $\text{sim}(A, B)$  denotes the cosine-similarity-based alignment between tokens in  $A$  and their best matches in  $B$ . Higher values indicate stronger semantic grounding and better preservation of meaning.

**Prompt Cleanliness** measures the extent to which the generated story is free of **prompt-related artifacts** and **instruction leaks**, such as residual system directives, role indicators, formatting constraints, or meta-level indications. These artifacts indicate a failure of narrative abstraction, where the model collapses from storytelling to instruction-following behaviour, severely degrading readability. The generated text is analysed line by line and sentence by sentence using a set of high-precision regular expression patterns anchored to sentence or line boundaries. A contamination score  $C$  is computed as:

$$C = \frac{1.0 \cdot N_{\text{line}} + 0.75 \cdot N_{\text{sent}} + 1.25 \cdot N_{\text{json}} + 0.75 \cdot N_{\text{fence}} + 2.5 \cdot N_{\text{block}}}{|L|} \quad (4)$$

where  $L$  denotes the set of non-empty lines in the generated text, and:

- $N_{\text{line}}$  is the number of lines beginning with explicit chat-role or instruction markers (e.g., Human :, Assistant :, Rules :);
- $N_{\text{sent}}$  counts sentences that exhibit imperative instruction patterns at sentence boundaries;
- $N_{\text{json}}$  denotes the number of lines consisting solely of structured JSON-like content;
- $N_{\text{fence}}$  counts occurrences of markdown code fences;
- $N_{\text{block}}$  counts dense instruction blocks characterized by multiple repeated occurrences of imperative constraints (e.g., three or more instances of “do not” within a single sentence or paragraph).

The weights associated with each term are selected empirically to prioritize the detection of severe leakage patterns over recall, assigning stronger penalties to artifacts that indicate a near-complete collapse into instruction-following mode. The score is clipped to the unit, as outputs exceeding this threshold are considered equally dominated by prompt artifacts. Prompt Cleanliness is then defined as:

$$\text{PromptCleanliness} = 1 - \min(1, C). \quad (5)$$

**Title Coverage** evaluates whether the generated story preserves the **section structure** of the original outline. Let  $\mathcal{O} = \{o_1, \dots, o_5\}$  denote the target section titles and  $\mathcal{G} = \{g_1, \dots, g_5\}$  the generated ones. We compute a soft similarity score and average it across sections:

$$TitleCoverage = \frac{1}{n} \sum_{i=1}^n \text{sim}(\text{norm}(g_i), \text{norm}(o_i)), \quad (6)$$

where  $n$  is the number of sections,  $\text{norm}(\cdot)$  removes differences in case, whitespaces, and punctuation, and  $\text{sim}(\cdot, \cdot) \in [0, 1]$  is a string similarity function (1 for identical titles, lower values for partial matches). This yields a graded measure of structural fidelity that is robust to minor formatting differences.

**No Redundancy** is a **fluency indicator** that penalizes degenerative loops and excessive reuse of the same textual fragments, which are common artifacts in long-form generation. Repetition is quantified by computing the frequency of word-level  $n$ -grams in the generated story, with  $n = 3$  (trigrams), which provide a robust balance between sensitivity to repetition and tolerance to natural phrasing. Let  $\mathcal{G}_n$  denote the multi-set of all  $n$ -grams extracted from the narrative, the repetition rate is defined as:

$$RedundancyRate = \frac{\max_{g \in \mathcal{G}_n} \text{freq}(g)}{|\mathcal{G}_n|}, \quad NoRedundancy = 1 - RedundancyRate. \quad (7)$$

High values of *NoRedundancy* indicate fluent, varied text with minimal looping or redundant phrasing. This formulation is designed to capture obvious degenerative loops rather than fine-grained stylistic repetition, prioritizing robustness and interpretability over sensitivity to subtle discourse patterns.

**No Hallucination** quantifies the inclusion of entities that are not supported by the source material. After a post-processing normalization step applied to extracted entities (e.g. lowercasing, removal of possessive suffixes), we perform a NER-based comparison: the generated story is analyzed using SpaCy [21] to extract entities of type PERSON and ORG, which are then matched against the entities detected in the source paper. The restriction to these entity types is deliberate: in our manual qualitative inspection of generated outputs, hallucinations most frequently manifested as invented author names and institutional affiliations, making PERSON/ORG the most relevant entity types for a stable automatic signal. Any entity appearing in the story but absent from the source material is treated as a hallucination. A broader discussion of alternative hallucination detectors, along with their limitations and the decision of why this is the approach used, is provided in Section 5. Formally, let *GeneratedEntities* be the set of PERSON/ORG entities extracted from the story, and *HallucinatedEntities* the subset of those not found in the paper, the score is defined as:

$$NoHallucination = 1 - \frac{|HallucinatedEntities|}{|GeneratedEntities|}. \quad (8)$$

A higher value indicates stronger factual alignment with the source document.

## 5. Hallucination Detection in Scientific Storytelling

A key challenge in AI-based story generation from source documents is assessing whether generated narratives remain faithful to the underlying material without introducing unsupported entities or claims. Unlike summarization, storytelling intentionally involves simplification, contextualization, and narrative adaptation, producing an expected and desirable creative divergence. The core challenge is in distinguishing *legitimate narrative abstraction* from *true factual hallucination*, a distinction that existing hallucination detection methods (largely designed for summarization) are not well equipped to make.

In this setting, hallucination cannot be reduced to mere deviation from the source text: a story may remain faithful while employing metaphors, analogies, or contextualization absent from the original paper. This inherent ambiguity makes hallucination detection particularly challenging and motivates the comparison of multiple detection approaches.

**Capitalised Words as Entity Proxies.** This approach is deliberately simplistic: any word starting with a capital letter is treated as a potential factual entity. If such a token appears in the story but not in the article, it is marked as hallucination. This heuristic reveals clear limitations:

- abbreviations in the story (e.g. “AI”) are flagged if the source document only contained the expanded form (e.g. “Artificial Intelligence”),
- metaphors or narrative constructs capitalised for emphasis are misclassified as entities,
- minor morphological variants (pluralisation, genitives) produce false positives.

Although rudimentary, this method lays the foundation for understanding the structure of the problem: hallucination detection must separate surface-form noise from true semantic divergence.

**NER-Based Detection (SpaCy PERSON/ORG).** In this approach, we leverage SpaCy to only detect named entities of types PERSON and ORG, as described in Section 4 and Equation 8. This significantly reduces the number of irrelevant candidates and detects genuinely invented organisations or people introduced by the model. Nevertheless, NER remained a shallow signal: it can detect incorrect affiliations, but fails to identify deeper factual inconsistencies, e.g. wrong scientific claims, invented datasets, or unsupported causal statements. We specifically focus on PERSON/ORG because our qualitative analysis repeatedly found fabricated authors and affiliations to be the most frequent and disruptive hallucination pattern in our stories.

**MIRAGE Rewrite-Consistency Scoring.** MIRAGE is an open-source library for hallucination detection based on rewriting the same passage multiple times and measuring the stability of the appearing concepts [22]. If an idea disappears or mutates across rewrites, MIRAGE treats it as hallucinated. Although effective in summarization, this approach does not transfer well to persona-oriented storytelling. As revealed by our experiments, MIRAGE consistently and incorrectly flags explanatory metaphors (e.g., introducing a system by analogy with a familiar real-world process that is not explicitly described in the paper) and rephrasing for non-expert audiences (e.g., replacing technical terminology with higher-level conceptual descriptions). This indicates a misalignment between MIRAGE’s operational definition of fidelity, centred on literal grounding, and the goals of narrative systems that intentionally simplify the source material.

**LLM-as-a-Judge.** We use an LLM to judge hallucinations directly. The judge receives the full scientific article as CONTEXT, the story as ANSWER, and produces a structured JSON verdict that includes faithfulness, hallucinated entities and numerical errors. This brings a qualitative leap because the LLM can reason about paraphrases and understand the broader context.

A first experiment conducted with the Qwen-7B model [20] has shown two systematic patterns:

1. **Missed hallucinations:** Some fabricated facts (e.g. invented institutional affiliations) are left undetected.
2. **False positive:** In several cases, it labeled hallucinated entities that were explicitly supported by the source paper (and mentioned in the story), i.e., the judge itself hallucinated the hallucination.

In short, the judge sometimes *hallucinates hallucinations*, making it too unreliable to serve as a scoring component.

A second experiment used the GPT 5.1 model [23]. While its assessments were more consistent with human judgment, the model remained overly strict, labelling benign contextual expansions as hallucinations merely because the source material did not explicitly mention those cases.

**Hybrid Hallucination Detection (HHD).** A collection of some positive results from previous discoveries are combined together to form a hybrid technique consisting to:

1. extract “technical tokens” via SpaCy (capitalised words, acronyms, numbers),

2. retrieve the top- $k$  most similar sentences from the article using MiniLM embeddings [24],
3. mark a token as hallucinated only if it appears in none of the retrieved contexts *and* the similarity score is below a threshold.

This approach combines symbolic robustness (entity extraction), semantic flexibility (retrieval-based context), and local grounding (sentence-level comparison), but is difficult to calibrate: if the threshold is too low, subtle hallucinations pass undetected; if too high, creative paraphrases are over-penalised.

We qualitatively analysed the Hybrid Hallucination Detector (HHD) across three papers and their generated story sections. Manual inspection showed that false positives dominate the detector’s output, mainly due to pedagogical reformulations that are conceptually faithful but not literally supported by retrieved sentences. For example, the following excerpt is from a generated story about [25]:

*Hermes, the messenger god of ancient Greece, was known for his speed and efficiency. Similarly, the HERMES system acts as a swift messenger between the initial prompt and the final, refined medical image segmentation.*

In this case, *HERMES* is the name of a framework, introduced through a creative but semantically correct analogy, yet incorrectly flagged as hallucinated. Conversely, false negatives occurred when the retrieval step returned semantically adjacent but non-supportive contexts. Taking another example from the same story:

*The proposed solution is an automated framework designed to enhance the accuracy of flash memory (FM)-based segmentation.*

The original paper used the acronym *FM* to refer to *Foundation Models*, but not *Flash Memory*, resulting in an undetected hallucination.

Overall, the method proved too sensitive to surface mismatch and too permissive to semantic drift. Because these two error types move in opposite directions, tuning the threshold did not lead to a stable operating point, making HHD unsuitable as a scoring component for StoryScore.

Method	What it detects	Strengths	Weaknesses
Capitalised Words	Surface-form mismatch	Simple, transparent	Noisy; overflags creativity
SpaCy NER	Incorrect entity mentions	Good precision	Misses conceptual hallucinations
MIRAGE	Rewrite instability	Captures semantic drift	Penalises analogies
LLM-as-Judge (Qwen)	Factual consistency	Understands paraphrases	Inconsistent; invents hallucinations
LLM-as-Judge (GPT 5.1)	High-level reasoning errors	Close to human judgement	Too strict for storytelling
HHD	Entity + retrieval alignment	Balanced approach	Unstable thresholds; mixed reliability

**Table 2**

Comparison of explored hallucination detection methods.

Table 2 summarizes our findings on different hallucination detection techniques. From our experiments, employing these techniques on the use case, two key outcomes emerged. First, The most operationally stable detector was the simplest one, namely the NER-Based detection, combined with regex normalisation. In particular, it was the only method that: 1. remained stable across papers, showing consistent behaviour across different documents, 2. did not penalise metaphors, 3. detected genuine fabricated entities, and 4. integrated cleanly with a software pipeline, without the need of external and costly API calls. Second, hallucination must have a reduced weight in the overall metric. Since all methods exhibited weaknesses, either too naive (NER), too strict (MIRAGE), or too unstable (LLM judge), its contribution to StoryScore was reduced from 0.2 (which was initially planned) to 0.1. This ensures that hallucination detection informs the metric without overshadowing the other reliable qualities.

## 6. Preliminary Findings

We apply StoryScore to the stories generated by our use-case pipeline (Section 3) on the full test set, in order to assess whether the metric behaves consistently beyond a small illustrative subset.

Table 3 reports aggregated statistics across the test set (76 generated stories) comparing two versions of the pipeline, using either a pre-trained version of Qwen2.5, or a fine-tuned version of the model. Fine-tuning substantially improves StoryScore and Context Recall, and completely eliminates prompt leakage, while other components show more moderate gains. Prompt Cleanliness and Title Coverage saturated on the test set, but their presence in StoryScore is a diagnostic safeguards. No Redundancy and No Hallucination exhibit higher variance, reflecting the sensitivity of long-form generation to repetition artifacts and entity-level unsupported mentions. Nevertheless, the pre-trained model still attains positive scores, particularly on BERTScore, Title Coverage, No Redundancy, and No Hallucination.

LLM version	StoryScore	BERTScore	Context Recall	Prompt Cleanliness	Title Coverage	No Redundancy	No Hallucination
Pre-trained	0.560	0.780	0.390	0.011	0.990	0.893	0.957
Fine-tuned	0.787	0.815	0.472	1.000	0.998	0.903	0.925

**Table 3**

StoryScore components on the test set, comparing the pre-trained and fine-tuned versions of the pipeline.

We conducted a manual inspection and consistently found that narratives generated in the pre-trained settings are affected by prompt leakage, redundancy, and excessive narrative filler, deficiencies that are only weakly penalized by global semantic metrics. BERTScore operates at the embedding level and is tolerant of paraphrasing, repetition, and generic formulations, allowing long and semantically “safe” texts to achieve high scores despite being poorly readable or editorially unacceptable. Conversely, the fine-tuned model generates more controlled, dense, and readable narratives, yet these qualitative improvements are only partially reflected in metrics. Among the components, Context Recall aligns most clearly with qualitative analysis. Its relatively low values reflect the task’s emphasis on synthesis and reformulation rather than lexical reuse; lower scores for the pre-trained model are consistent with its greater reliance on generic fillers that weaken lexical grounding. Overall, variations in StoryScore were consistent with qualitative judgments of readability, narrative control, and factual grounding.

## 7. Conclusions and Future Work

This paper addressed the problem of evaluating AI-generated scientific stories, a task that combines factual grounding with narrative transformation and persona adaptation. We introduced StoryScore, a composite metric that integrates semantic alignment, lexical grounding, structural fidelity, fluency, and hallucination control, and analysed its behaviour on a concrete scientific storytelling use case. Our analysis shows that different metrics capture complementary but uneven aspects of narrative quality. While embedding-based measures reliably assess semantic similarity, they remain largely insensitive to discourse-level control issues such as redundancy, prompt leakage, and narrative structure. The combination of complementary metrics provides a more informative picture of system behaviour than any single score alone. Overall, the initial evaluation suggests that the automatic metrics composing StoryScore are useful for comparisons between generated stories, even if insufficient for discriminating critical aspects of narrative quality and text control in an absolute way.

Hallucination detection proved to be an intrinsically complex task, even more when creativity and pedagogical reformulation are involved. Existing hallucination detection approaches are either too shallow, too rigid, or too unstable. Future evaluation frameworks should explicitly account for persona adaptation and narrative transformation, calling for a new definition of hallucination that distinguish

between acceptable abstraction and factual distortion. Finally, this work motivates further refinement of composite metrics such as StoryScore – particularly through the inclusion of components explicitly targeting narrative control and structural validity – as well as an assessment of alignment with human judgement following some best practices [13].

## Declaration on Generative AI

During the preparation of this work, the authors used GPT5.2 for grammar and spelling check. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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