The Reader is the Metric: How Textual Features and Reader Profiles Explain Conflicting Evaluations of AI Creative Writing

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Abstract

Recent studies comparing AI-generated and human-authored literary texts have produced conflicting results: some suggest AI already surpasses human quality, while others argue it still falls short. We start from the hypothesis that such divergences in literary evaluation are a meaningful signal. We posit that perceived "quality" is not a single, static property of a text, but emerges from the interaction between the text's features and the reader's own evaluative criteria. Using five public datasets (1,471 stories, 101 annotators including critics, students, and lay readers), we (i) extract 17 reference-less textual features (e.g., coherence, emotional variance, average sentence length...); (ii) model individual reader preferences, deriving feature importance vectors that reflect their textual priorities; and (iii) analyze these vectors in a shared "preference space". Reader vectors cluster into two profiles: *surface-focused readers* (mainly non-experts), who prioritize readability and textual richness; and *holistic readers* (mainly experts), who value thematic development, rhetorical variety, and sentiment dynamics. Our results quantitatively explain how measurements of literary quality are a function of how text features align with each reader's preferences. These findings advocate for reader-sensitive evaluation frameworks in the field of creative text generation.[1]

1 Introduction

Large Language Models (LLMs) are increasingly able to generate short stories that resemble human writing, leading to a growing number of evaluation studies based on reader judgments. As Table 1 shows, the results of such studies are mixed. Some find that lay readers often prefer AI-generated texts—even over canonical authors like Shakespeare (Porter and Machery, 2024)—or rate a small language model above the average human writer in creative tasks (Marco et al., 2025). Others find that expert judges consistently favor human texts. Critics rank Patricio Pron's stories above those written by GPT-4 (Marco et al., 2024), human-written texts satisfy far more creativity criteria in the Torrance Test (Chakrabarty et al., 2024). Gómez-Rodríguez and Williams (2023) find a mixed picture: top commercial LLMs match or even surpass humans in fluency and coherence, but humans keep the edge in creativity and nuanced humour. What drives these apparently opposing judgments, and can this variation be measured in a systematic way? Answering this question is the core motivation of our work.

A common approach in these studies is to aggregate ratings to establish a consensual measure of literary quality for an evaluative group. By design, this process averages out individual differences to identify a shared standard. Our work, however, adopts a perspectivist view (Plank, 2022; Bizzoni et al., 2022a), focusing specifically on this variation as a meaningful signal.

While many factors can influence literary judgment, including references to other texts, political alignment, or familiarity with genre conventions, this study focuses on intrinsic textual features: measurable properties related to style, structure, and content. These features provide a reasonable starting point for modeling variation in reader preferences, as they can be extracted directly from the text and interpreted consistently across corpora.

Inspired by multi-criteria decision-making theory (Triantaphyllou, 2000), we conceptually frame each reader's evaluation as an additive utility function over textual features. For each reader, we estimate a weight vector that best predicts their observed rankings, providing an interpretable representation of their literary priorities. This approach provides a quantitative basis for explaining preference variability, allowing us to characterize the

[1]Code, data, and results: `https://github.com/grmarco/the-reader-is-the-metric`

Findings of the Association for Computational Linguistics: ACL 2025, pages 25432–25449

Paper	AI writer	Human Writers	Assessors	AI surpass Humans
(Marco et al., 2025)	SLM	Average Writers	Average Readers	✓
(Porter and Machery, 2024)	LLM	Top Writers	Average Readers	✓
(Gómez-Rodríguez and Williams, 2023)	LLM	Writing Students	Writing Students	≈
(Chhun et al., 2024)	LLM	Average Writers	LLM	=
(Chakrabarty et al., 2024)	LLM	Professional Writers	Literary Experts	×
(Marco et al., 2024)	LLM	Professional Writers	Literary Experts	×

Table 1: Comparison of AI-generated text performance against human writers.

observed gap between expert and non-expert evaluations by modeling the distinct features each group prioritizes.

To guide our investigation into these aspects, this work seeks to answer four research questions: **(RQ1)** Do AI and human stories differ in measurable textual features across datasets? **(RQ2)** Can reader preferences be modeled from these features? **(RQ3)** Do experts and non-experts prioritize different features? And **(RQ4)** do these preference patterns remain consistent across datasets?

In addressing these research questions, this paper makes the following contributions:

- We compile and implement an open-source set of interpretable, reference-less textual metrics that capture stylistic, structural, and semantic properties relevant to literary judgment.

- We introduce a method to model reader preferences as weighted combinations of the above textual metrics, enabling interpretable analysis of audience-specific judgment.

- Analyzing five public datasets, we show that AI-generated texts gain favor when their feature profiles align with reader-preferred textual characteristics, which in some cases overlap with or emulate features found in valued human-authored stories.

- We demonstrate that individual reader preferences, when modeled from textual features, cluster into distinct evaluative profiles that subsequently show a strong correlation with reader expertise. Specifically, emergent clusters reveal two primary reader types: one, largely composed of lay readers, prioritizes linguistic richness and textual accessibility (e.g., sentence complexity, readability, lexical diversity). The other, predominantly comprising experts, assigns greater weight to thematic development, expressive stylistics, and sentiment arcs. These emergent, divergent evaluative criteria are identified as a key factor in explaining the conflicting results observed in prior studies comparing AI and human writing.

2 Related Work

Research at the intersection of Artificial Intelligence (AI) and literature has explored several key areas. A prominent line of work directly compares the perceived quality of AI-generated and human-authored texts, often framing the comparison as a competition (Gómez-Rodríguez and Williams, 2023; Porter and Machery, 2024; Chakrabarty et al., 2024; Marco et al., 2024, 2025). These studies reveal a complex picture, with outcomes varying significantly depending on the type of text (e.g., poetry vs. short stories), the expertise of the evaluators (e.g., average readers vs. literary critics), and the specific AI models employed. For instance, some studies indicate that AI-generated texts are sometimes preferred by lay readers (Marco et al., 2025; Porter and Machery, 2024), while others, particularly those involving literary experts, consistently show a preference for human-authored texts (Marco et al., 2024; Chakrabarty et al., 2024).

Building on the observation of varied outcomes in quality perception, recent research delves deeper by quantifying specific aspects like creativity. The "Creativity Index," for instance, assesses linguistic originality by how much a text can be reconstructed from web snippets, revealing that professional human authors exhibit a 66.2 % higher index than LLMs (Lu et al., 2024). Furthermore, the process of aligning LLMs with human preferences through methods like RLHF has been shown to inadvertently reduce their Creativity Index by about 30.1% (Lu et al., 2024; Yu et al., 2025). This observation implies a trade-off: enhancing safety or coherence might occur at the expense of originality (Yu et al., 2025), a dynamic particularly relevant when considering how different reader profiles, especially experts valuing originality, might assess these outputs.

The current work builds upon a foundation of research in computational literary studies that seeks to identify textual correlates of literary quality. Studies have explored how features such as global coherence, local unpredictability, sentiment arcs, and emotional volatility differentiate between canonical literature, bestsellers, and other categories (Bizzoni et al., 2024a; Feldkamp et al., 2024; Bizzoni et al., 2024b; Moreira et al., 2023). These insights inform the selection of our implemented textual metrics. However, our study does not directly use these metrics to predict literary quality. Instead, they are leveraged to model how individual readers differentially weight these properties, reflecting their unique quality model.

The importance of perspectivism in literary evaluation has been emphasized in prior work. Bizzoni et al. (2022a) propose a "mild perspectivist" approach that aggregates literary judgments within socially or professionally coherent reader classes. They show that each class yields internally consistent quality judgments and argue that such reader classes are the natural unit for modelling literary value. Our study extends this perspectivist view by modeling reader preferences at the individual level, not based on predefined categories, but inferred directly from annotated comparisons and textual features. This enables a finer-grained, data-driven reconstruction of evaluative profiles, which can then be clustered to reveal latent reader types without pre-established assumptions.

3 Problem Definition

We consider a collection of t texts $\mathcal{T} = \{x_1, x_2, \ldots, x_t\}$, each described by a d-dimensional vector of intrinsic, reference-less features

$$\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \in \mathbb{R}^d,$$

capturing several dimensions related to coherence, originality, readability, sentiment arcs, and stylistic complexity (detailed in Section 4.2).

Additionally, we have a set $\mathcal{L} = \{r_1, r_2, \ldots, r_l\}$ of l readers. Each reader $r_j \in \mathcal{L}$ provides evaluations for texts x_i. These diverse raw evaluations (e.g., multi-dimensional Likert scores, collections of binary judgments) are first aggregated into a single raw preference score $S_j(x_i)$ for each text x_i evaluated by reader r_j. To enable comparison across heterogeneous scales and readers, these raw scores $S_j(x_i)$ are then mapped to a continuous *preference value* $\rho_j(x_i) \in [0, 1]$ via per-reader min-max normalisation:

$$\rho_j(x_i) = \frac{S_j(x_i) - S_j^{\min}}{S_j^{\max} - S_j^{\min}}, \tag{1}$$

where $S_j^{\min}$ and $S_j^{\max}$ are the minimum and maximum raw preference scores $S_j(\cdot)$ assigned by r_j within that dataset. Sorting texts by $\rho_j(x_i)$ yields a reader-specific ranking π_j.

Reader Preference Centroid For each reader r_j, their reader preference centroid or "paradigmatic text" is profiled by $\mathbf{x}_j^*$, the $\rho_j(x_i)$-weighted average of features from their top-rated texts X_j^{top} (e.g., top 25% of their evaluations):

$$\mathbf{x}_j^* = \frac{\sum_{x_i \in X_j^{top}} \rho_j(x_i)\, \mathbf{x}_i}{\sum_{x_i \in X_j^{top}} \rho_j(x_i) + \epsilon}. \tag{2}$$

These profiles capture preferred textual characteristics within a specific dataset.

Reader Utility Model Inspired by multi-criteria decision-making theory (Triantaphyllou, 2000), we posit that each reader implicitly combines textual features through an *additive utility function*:

$$U_j(x_i) = \sum_{f=1}^{d} w_{jf}\, x_{if}, \tag{3}$$

where $\mathbf{w}_j = (w_{j1}, \ldots, w_{jd}) \in \mathbb{R}^d_{\geq 0}$ encodes the conceptual importance reader r_j assigns to feature f. A higher $U_j(x_i)$ indicates better alignment with r_j's preferences. Eq. 3 serves as a conceptual starting point; practical estimation could implement non-linear models (as we do in Section 4) to derive empirical proxies for $\mathbf{w}_j$ as feature importances.

This formalisation sets the stage for our empirical study: (1) characterizing human- and AI-authored texts within their shared feature space to examine their properties and interrelations, and (2) inferring reader-specific preferences (via proxies for $\mathbf{w}_j$ and profiles $\mathbf{x}_j^*$) to analyse patterns of literary preference.

4 Methodology

Our methodology proceeds by: (1) analyzing the datasets and extracting textual features; (2) processing reader evaluations into unified preference scores and pairwise data; (3) conducting an exploratory analysis of text features and initial reader preferences to predict preferences (RQ1); and (4) training individualized Random Forest models (RQ2), from which feature importances are extracted and clustered to identify reader profiles (RQ3-4). These steps are detailed below.

4.1 Data: Corpora & Annotation Design

The five datasets selected for this study offer complementary perspectives on human evaluation of AI-generated literary texts. Each provides explicit reader-level judgments, includes both AI- and human-authored short narratives, and retains the full textual content for feature extraction. Table 2 summarizes the main characteristics of each one.

SLM (Marco et al., 2025) comprises 122 movie synopses written by either humans or a fine-tuned BART-large model (Lewis et al., 2020), evaluated by 68 lay readers across five dimensions: creativity, readability, relevance, understandability, and attractiveness. It compares the creative output of small language models with that of average human writers under varying disclosure conditions regarding the author's.

HANNA (Chhun et al., 2022) contains over 1,000 narrative texts, each evaluated by ten Mechanical Turk workers along multiple 5-point Likert scales—such as fluency, coherence, and overall quality.

CONFEDERACY (Gómez-Rodríguez and Williams, 2023) 65 short stories (250-1200 words) from a single prompt, 5 human-authored, 60 AI-generated (5 per model from 12 LLMs). Each rated by 2 independent raters on 10 dimensions (1300 ratings total).

PRONVSPROMPT (Marco et al., 2024) comprises 180 fictional film synopses of approximately 600 words. Sixty were authored by Spanish writer Patricio Pron, and 120 were generated by GPT-4. Six literary experts—editors, scholars, and instructors—evaluated 120 stories each, blind to authorship. Their assessments followed a rubric grounded in Margaret Boden's theory of creativity (Boden, 2004), rating dimensions such as originality, narrative voice, and attractiveness.

TTCW (Chakrabarty et al., 2024) consists of 48 short stories derived from 12 one-sentence plot prompts. For each prompt, one human-authored story from *The New Yorker* and three AI-generated stories (by GPT-3.5, GPT-4, and Claude 1.3) were produced, yielding 36 machine texts and 12 human texts. Each story was evaluated by three experts—creative writing professors, literary agents, and MFA-trained authors—using a 14-item binary rubric adapted from the Torrance Test of Creative Thinking (TTCT), covering fluency, flexibility, originality, and elaboration.

4.2 Feature Extraction

To characterize the short stories, we selected a set of reference-less metrics grounded in prior work on literary text evaluation and stylometric analysis (Celikyilmaz et al., 2020; Bizzoni et al., 2022b; Feldkamp et al., 2024). Rather than prescriptive quality indicators, these metrics are descriptive features designed to capture salient textual properties. We selected them based on three criteria: (1) theoretical relevance to literary characterization, (2) interpretability, and (3) low redundancy (Pearson $|r| < 0.7$, see Appendix B), which ensures a diverse yet concise feature set and mitigates multicollinearity. The selected metrics, formally defined in Appendix A, encompass:

- **Linguistic fluency and readability**: including *average sentence length* as a basic measure of syntactic load; the *SMOG index* (McLaughlin, 1969) for syllable-based readability assessment; and *MTLD* (McCarthy and Jarvis, 2010) for a measure of lexical diversity.

- **Structural and thematic coherence**: such as *entity coherence*, which models narrative continuity based on entity-grid transitions (Barzilay and Lapata, 2008); *local coherence embeddings*, assessing semantic linkage between adjacent sentences using their distributed representations (Li and Hovy, 2014); as well as *thematic graph density* and *thematic entropy*, which quantify the connectivity (Newman, 2010) and diversity (Shannon, 1948) of topical structures discovered via Latent Dirichlet Allocation (Blei et al., 2003; Röder et al., 2015).

- **Sentiment dynamics**: including *average sentiment*, *sentiment variance*, and *emotional volatility*. These reflect the overall tonal polarity and its consistency, alongside the variability of dominant emotions across the narrative arc, as identified by fine-tuned RoBERTa-based models (Hartmann et al., 2023; Demszky et al., 2020; Liu et al., 2019).

- **Originality and Predictability**: approximated by the *log-likelihood* of

Alias	# Texts	AI/H	# Readers	Scale	Annotator BG	Source
SLM	122	61/61	68	7-pt Likert	Lay (MSc students)	Marco et al. (2025)
HANNA	1 056	960/96	10	5-pt Likert	Lay (MTurk)	Chhun et al. (2022)
CONFEDERACY	65	60/5	10	10-pt Likert	Lit. students	Gómez-Rodríguez and Williams (2023)
TTCW	48	36/12	7	14-item bin.	Critics / writers	Chakrabarty et al. (2024)
PRONVSPROMPT	180	120/60	6	7-pt Likert	Critics	Marco et al. (2024)

Table 2: Corpora used to model reader preferences. "AI/H" is the split between AI-generated and human-authored texts. Full corpus statistics, including total pairwise comparisons and AI-preference rates, are in Appendix C.

the text under a large language model (`meta-llama/Llama-3.2-3B-Instruct`; (AI at Meta, 2024)). Lower predictability is taken as an indicator of greater textual originality.

While the feature set does not cover higher-order literary constructs—such as narrative framing, ideological alignment, or intertextual reference—it provides a simple, transparent and replicable foundation for approximating reader preferences across diverse corpora.

4.3 Deriving Reader-wise Preference Data

As outlined in Section 3, raw reader evaluations $S_j(x_i)$ are first processed into an aggregated form. The specific aggregation method for $S_j(x_i)$ varies by dataset:

- For datasets with multi-dimensional Likert-scale evaluations (SLM, HANNA, CONFEDERACY, PRONVSPROMPT), $S_j(x_i)$ is the sum of scores across all evaluated dimensions for text x_i by reader r_j.
- For datasets with binary verdicts on $N_{criteria}$ criteria (e.g., TTCW), $S_j(x_i)$ is the count of positive ("Yes") verdicts.

These aggregated raw scores $S_j(x_i)$ are then min-max normalized per reader to yield continuous preference values $\rho_j(x_i) \in [0, 1]$ using Eq. 1. These $\rho_j(x_i)$ values are subsequently used to compute reader preference centroids (Section 4.4) and serve as the basis for generating pairwise preference data used in training our individualized learning-to-rank models, a process detailed in Section 4.5.

4.4 Exploratory Analysis and Reader Preference Centroids (RQ1)

To investigate RQ1 concerning systematic differences between AI-generated and human-authored texts and their relation to initial reader preferences, we first compute each reader r_j's reader preference centroid $\mathbf{x}_j^*$. This vector, calculated as per its formula (Eq. 2) using the derived preference values $\rho_j(x_i)$ (Section 4.3), represents r_j's Reader Preference Centroid. Crucially, these $\mathbf{x}_j^*$ profiles are defined within the d-dimensional text feature space of a specific dataset, reflecting r_j's high-preference textual characteristics within that particular corpus.

Subsequently, we employ Principal Component Analysis (PCA) for exploratory visualization. We project all text feature vectors $\mathbf{x}_i$ onto a common low-dimensional space (typically $\mathbb{R}^2$) to examine AI vs. human text distributions. PCA loadings help identify key differentiating features. Onto this same space, we project the dataset-specific reader preference centroid $\mathbf{x}_j^*$ to observe how these reader-preferred text characteristics align with the global text distributions. This combined visualization provides initial insights for RQ1 (detailed in Section 5.1).

4.5 Learning Individualized Preference Models (RQ2)

While Text Reader Centroids are insightful for understanding which specific textual features are valued in a given context, these dataset-specific profiles do not directly allow for comparison of underlying preference *structures* across different corpora (RQs2-4); this motivates the subsequent learning of individualized preference models. The primary challenge in learning these preference models lies in the nature of the available data: many readers have evaluated only a limited number of texts (see Table 2), making direct ranking functions difficult to train robustly due to sparse per-reader evaluations. Thus, we use a supervised pairwise learning-to-rank approach, a common strategy that converts ranking to binary classification.

To generate the training data for this classification task, we use the normalized preference values $\rho_j(x_i)$ derived in Section 4.3. Specifically, for each reader r_j and any two distinct texts x_a, x_b they evaluated where $\rho_j(x_a) \neq \rho_j(x_b)$, we generate balanced training instances: $(\mathbf{x}_a - \mathbf{x}_b, 1)$ if $\rho_j(x_a) > \rho_j(x_b)$ (and its opposite $(\mathbf{x}_b - \mathbf{x}_a, 0)$), or vice-versa. Pairs with equal preference scores ($\rho_j(x_a) = \rho_j(x_b)$) are discarded.

For each such pair, we derive the feature difference $\mathbf{x}_a - \mathbf{x}_b \in \mathbb{R}^d$. We then train a separate Random Forest classifier (Pedregosa et al., 2011; Breiman, 2001) for each reader r_j using these difference vectors and their corresponding binary preference labels. Initially, we tested Logistic Regression and Random Forest. Random Forest outperformed Logistic Regression, achieving higher F1 scores on the test set (Appendix B). Likely, literary judgment does not emerge from linear relationships between textual features but rather from non-linear relationships and complex feature interactions, which Random Forest better approximates.

4.6 Interpreting Preferences and Identifying Reader Profiles (RQ3-4)

Once a Random Forest model is trained for each reader r_j, we extract feature importance values to determine which attributes were most influential in distinguishing $\mathbf{x}_i$ from $\mathbf{x}_{i'}$. Specifically, we use the mean decrease in impurity (MDI) which measures how much each feature reduces the weighted impurity (Gini entropy) across all trees in the forest (Breiman, 2001). These importance values serve as empirical proxies for the conceptual weights w_{jf} in the additive utility model discussed in Section 3, providing an interpretable, albeit approximated, representation of the reader's preference structure. Clustering these importance vectors across many readers enables us to uncover shared patterns in literary judgment.

In summary, our methodology integrates an exploratory stage, where PCA is used to examine textual feature distributions, and a second stage in which we train individualized pairwise preference models to learn generalizable evaluative patterns and quantify the importance of textual features for each reader across datasets.

5 Results and Discussion

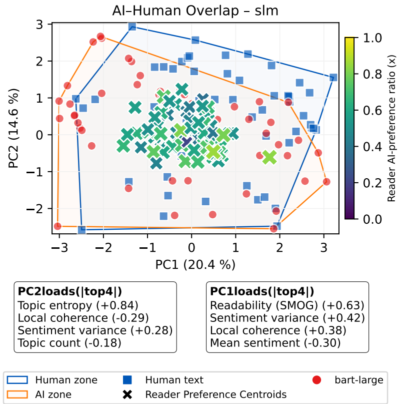
In this section, we examine whether AI- and human-authored texts differ measurably in their feature distributions, how these distributions relate to reader preferences, and whether reader-specific models can capture consistent patterns of evaluation. We structure the analysis around our four research questions.

5.1 Textual Separability, Feature Space Topography, and AI Preference Ratios

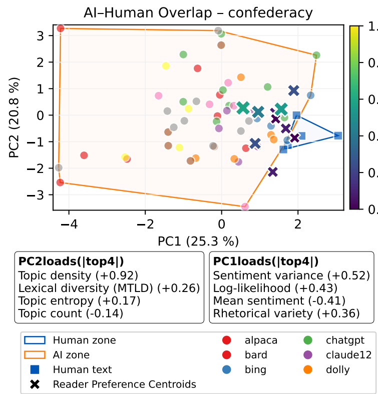
To assess differences between AI and human stories in measurable textual features and their relation to reader preferences (RQ1), we projected intrinsic story features from five datasets onto their first two principal components (PCA) (Figure 1). These visualizations delineate 'AI zones' and 'Human zones' using convex hulls, with 'Reader Preference Centroids' (crosses) indicating aggregate preference tendencies for each reader.

In the SLM dataset (Figure 1a), PC1 (20.4% variance) is driven by *Readability (SMOG)* (+0.63) and *Sentiment variance* (+0.42), while PC2 (14.6% variance) is primarily influenced by *Topic entropy* (+0.84). An extensive feature space overlap is observed between human-authored texts and those from the `bart-large` model. Reader Preference Centroids (crosses) are notably concentrated within this central overlapping region. A visual inspection suggests that the `bart-large` model generated more texts that fall into this main area of overlap. While approximately 22 of the 61 human texts appear distributed outside this primary overlapping zone, with many populating the distinct upper-right quadrant (characterized by lower local coherence and higher topic entropy, as indicated by PC2 loads), only around 11 of the 61 AI-generated texts seem similarly dispersed. Consequently, AI effectively "placed" more texts (approximately 50 out of 61) within this central overlapping feature space, compared to human authors (approximately 39 out of 61). Given that reader preferences are densely clustered within this same overlapping area, the AI's greater presence in this zone—where texts may be perceived as indistinguishable or even preferable according to the metrics—likely explains its higher preference rate of 57.59%.

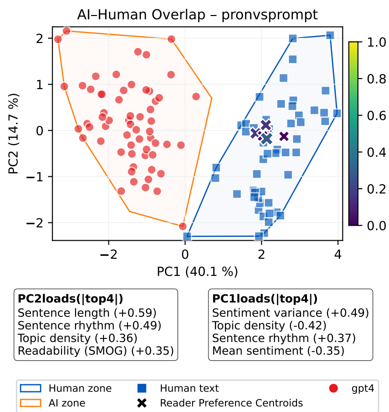
The CONFEDERACY dataset (Figure 1b) presents human texts forming a cohesive cluster in the positive PC1 region (characterized by high *Sentiment variance* (+0.52), *Log-likelihood* (+0.43), and *Rhetorical variety* (+0.36)) and the mid-to-low PC2 region (moderate *Topic density* (+0.92)). AI-generated texts are widely dispersed, resulting in minimal overlap between the 'Human zone' and the majority of the 'AI zone'. This clear separation, unlike in SLM, correlates with a lower AI preference (22.95%). The Reader Preference Centroids (crosses) indicate that while many preferences align



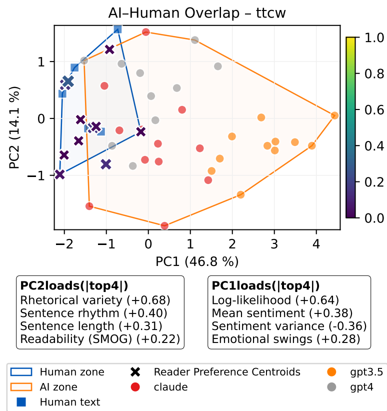
(a) SLM
AI preference: 57.59%



(b) Confederacy
AI preference: 22.95%



(c) PRONVSPROMPT
AI preference: 13.12%



(d) TTCW
AI preference: 2.16%

Figure 1: PCA projection of textual feature vectors for AI-generated and human-authored stories across four datasets (a-d), sorted by decreasing AI preference rate. Each point is a story. Axes (PC1, PC2) are principal components; adjacent boxes detail their top feature loadings. Convex hulls show 'AI' (orange) and 'Human' (blue/darker outline) textual feature zones, indicating overlap or separation. 'Reader Preference Centroids' (X marks) represent the average features of highly-rated stories for each reader; their size and color intensity correspond to the individual reader's AI preference ratio. The overall 'AI preference' percentage shows how often readers favored AI texts within that dataset. The figure illustrates how text separability and centroid alignment with these zones correlate with these AI preference rates across datasets.

with the human cluster, others are associated with specific AI texts. These preferred AI texts, though situated outside the primary human cluster, effectively emulate the strong positive PC1 characteristics (high sentiment variance and rhetorical variety) typical of the human-authored stories. Thus, in CONFEDERACY, AI preference appears driven not by general indistinguishability, but by the capacity of certain AI models to replicate specific, valued stylistic dimensions captured by PC1, which align with the evaluative criteria of the literature students.

PRONVSPROMPT (Figure 1c) shows pronounced separation. Human texts (Pron) cluster in the high positive PC1 region, characterized by high *Sentiment variance* (+0.49), marked *Sentence rhythm* (+0.37), lower *Topic density* (PC1 loading -0.42), and a less positive *Mean sentiment* (PC1 loading -0.35). Conversely, GPT-4 texts occupy the negative PC1 region. With 'Human' and 'AI' zones being almost entirely disjoint, and Reader Preference Centroids exclusively within the 'Human zone', the literary critics' strong alignment with Pron's distinct features results in a very low AI preference (13.12%).

In TTCW (Figure 1d), human texts form a distinct, compact cluster in the extreme negative PC1 region, signifying high LLM-based originality (*Log-likelihood* loading for PC1 is +0.64), a more neutral/negative *Mean sentiment* (PC1: +0.38), and high *Sentiment variance* (PC1: -0.36). These texts also show high PC2 values (*Rhetorical variety* (+0.68)). While most AI texts are in the positive PC1 space (more predictable, positive sentiment), a few Claude and GPT-4 instances fall within or near the 'Human zone', consistent with Chakrabarty et al. (2024) (Table 7). Despite this partial intrusion, Reader Preference Centroids remain almost exclusively with human texts, leading to a minimal AI preference (2.16%) by expert evaluators.

In summary, this cross-dataset analysis (RQ1) reveals a nuanced landscape regarding the differences between AI-generated and human-authored stories and their relation to reader preferences. Measurable differences in textual features do exist, but their nature and magnitude vary considerably depending on the specific AI models, human comparison texts, and evaluative contexts. Literary appeal emerges from a dynamic interplay between a text's measurable characteristics, the degree to which AI can replicate or align with human-valued features, and the specific evaluative lens of the reader.

5.2 Modeling Reader Preferences and Preference Clusters (RQ2)

To assess whether reader preferences can be modeled as weighted combinations of textual features, we first trained individual classifiers for each reader, as detailed in Section 4.6. For each reader, the trained classifier yields a feature importance vector, quantifying the relative weight each textual metric carries in predicting that reader's preferences. These individual feature importance vectors were then projected using PCA (Figure 2a) to visualize the overall landscape of reader preference structures and subsequently clustered via k-means ($k = 2$). The number of clusters was determined using standard validation techniques (see Section 4.6).

The resulting clusters exhibit a clear association with reader background, as shown by the distribution of readers per dataset across these clusters (Figure 2b). Readers from the SLM and HANNA datasets (both comprising general audiences) are predominantly grouped in Cluster 0. In contrast, readers from TTCW and PRONVSPROMPT (primarily literary critics and experts) largely fall into Cluster 1. The CONFEDERACY dataset, which includes literature students, shows a more mixed distribution across the two clusters, indicative of intermediate evaluation patterns.

These findings suggest that reader preferences reflect systematic, modelable tendencies that correlate with reader expertise. Crucially, these distinct preference clusters emerged solely from the modeling of evaluative judgments, without recourse to explicit reader metadata (such as self-declared expertise).

5.3 Feature Prioritization by Reader Type (RQ3)

Figure 3 visually contrasts the mean feature importance profiles for the two identified reader clusters. To understand the *direction* of these preferences, we cross-reference these importance scores with the mean feature values from Table 3 for texts typically favored by each reader type.

Cluster 0 (solid blue profile in Figure 3), mainly composed of lay readers (SLM, HANNA), emphasizes features related to linguistic complexity and textual accessibility. This group assigns notable importance to stylistic metrics such as *Max subordination depth*, *Sentence length*, *Syntactic depth*, and *Lexical diversity (MTLD)*. Analysis of the SLM dataset, where AI texts were often preferred by this cluster, shows these AI texts possessing, on average, higher maximum subordination, longer sentences, greater syntactic depth, and higher (less negative) MTLD scores (Table 3). The concurrent importance of *Readability (SMOG index)*, for which these preferred AI texts exhibit lower scores (indicating easier readability), suggests a valuation for elaborate and lexically rich prose presented within an accessible framework.

In contrast, Cluster 1 (red dashed profile in Figure 3), predominantly including literary critics and professional writers (TTCW, PRONVSPROMPT), prioritizes features capturing thematic richness, expressive stylistics, sentiment dynamics, and coherence. High importance is attributed to *Topic entropy*, *Sentence rhythm*, and *Rhetorical variety*. Human-authored texts, strongly favored by this cluster (Table 3), typically demonstrate higher thematic entropy and often more varied sentence rhythms. The importance of *Rhetorical variety* is high, though human texts are not always highest on this specific metric compared to all AI. Furthermore, the entire suite of sentiment features (*Mean sentiment*, *Sentiment variance*) is highly prioritized. Human texts preferred by this group exhibit more neutral or less overtly positive mean sentiment, and higher sentiment variance. *Local coherence* is also important; interestingly, human texts favored by experts show lower local coherence embedding scores, potentially reflecting an appreciation for more complex or less predictable local narrative transitions.

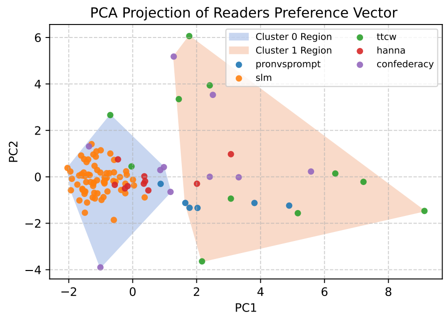
These divergent prioritizations, interpreted directionally using Table 3, directly address RQ3. Expert and non-expert readers weigh different textual dimensions and also exhibit preferences for specific feature levels. Non-experts (Cluster 0) favor texts with rich linguistic structure and good readability. Experts (Cluster 1) focus more on thematic development, expressive and varied stylistics, nuanced affective portrayal, and complex coherence patterns. The relatively similar importance assigned to *Log-likelihood* (originality) by both clusters in Figure 3 suggests it may be a generally valued characteristic. These distinctions underscore stable, interpretable differences in reader expectations.

Cross-Dataset Consistency (RQ4). The emergence of consistent textual distinctions (RQ1) and reader preference profiles (RQ2, RQ3) across the five diverse datasets underscores the stability and generalizability of our core findings. Crucially, the systematic clustering of reader preferences and their correlation with annotator expertise (RQ2) manifest despite the heterogeneity in prompts, AI models, and specific annotator groups across datasets.

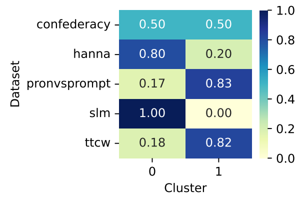
6 Conclusions and Future Work

This study demonstrates that literary quality judgments emerge from a structured interplay between a text's features and individual reader perception. We reveal two key drivers of literary preference: first, AI-generated stories gain favor when their textual profiles successfully emulate characteristics valued by specific reader groups, often aligning with features present in human-authored narratives that resonate with those readers; second, distinct reader communities consistently prioritize different textual dimensions. The preference for AI-generated texts, therefore, often hinges on their ability to exhibit the feature combinations favored by a particular reader profile.

These stable, divergent preference profiles across datasets suggest that the notion of a universal standard for "good writing" may be an oversimplification. Instead, our interpretable framework offers a path toward more nuanced evaluations of LLM-generated texts.



(a) The PCA projection of how readers cluster according to their preference vectors (k-means, with k = 2)



(b) Distribution of readers across clusters by dataset.

Figure 2: Clustering of users based on feature importance vectors. TTCW and PRONVSPROMPT, evaluated by literary critics, predominantly fall into Cluster 1. HANNA and SLM, both composed of lay readers, are mainly grouped in Cluster 0. CONFEDERACY, which includes writing students, shows a more balanced distribution across clusters, reflecting intermediate evaluation patterns.

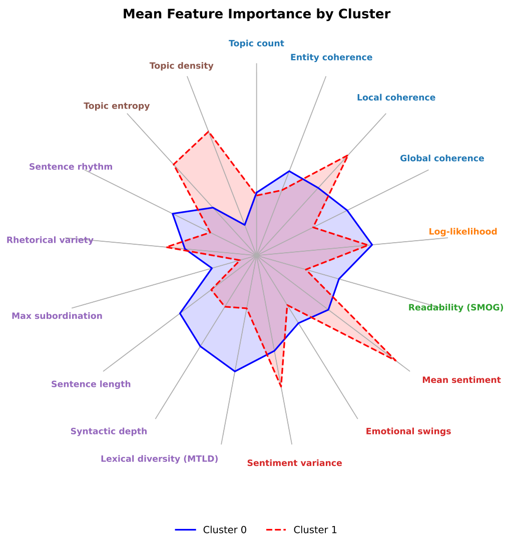


Figure 3: Radar chart illustrating the mean Random Forest feature importances for the two reader clusters. Higher values indicate greater importance assigned to a given textual feature when predicting preferences.

7 Scope and Limitations

This study investigates how literary preferences toward AI- and human-authored stories emerge from the interaction between intrinsic textual features and individual reader priorities. While our approach enables a systematic, interpretable, and reproducible analysis, it is not without limitations.

First, the analysis is restricted to short stories in English. Although this genre is central to many benchmark datasets, our findings may not generalize to other literary forms, such as poetry, drama, or long-form fiction, which exhibit different stylistic conventions and reader expectations. Genre-specific dynamics remain an open question for future work.

Second, all evaluations are conducted on pre-existing datasets involving blind annotations. While this controls for bias introduced by authorship awareness, it also limits our capacity to account for extratextual variables—such as prior exposure to AI-generated writing, cultural background, or ideological alignment, that may influence reader preferences. These factors likely play a role in real-world literary judgment but lie beyond the scope of this study.

Third, we rely on a curated set of textual features designed to capture stylistic, structural, and semantic properties. Despite efforts to ensure coverage and non-redundancy (Appendix B), some relevant dimensions of literary quality—such as narrative engagement, intertextuality, or affective resonance—remain challenging to operationalize.

Fourth, our preference models are trained on observational data. While they reveal systematic associations between reader types and feature weights, they do not establish causality. Experimental studies manipulating specific features while holding others constant would be needed to isolate causal effects.

Finally, although our clustering analysis identifies robust patterns aligned with reader expertise, the distinction between "expert" and "non-expert" is approximate and dataset-dependent. We define experts as literary professionals (critics, authors, professors), but this category may mask relevant differences in training, taste, or ideology. A finer-grained typology of evaluators is a promising direction for future work.

Acknowledgements

This work is partially funded by the Spanish Ministry of Science, Innovation and Universities (project FairTransNLP PID2021-124361OB-C32) funded by MCIN/AEI/10.13039/501100011033, and by a research agreement between UNED and Red.es (C039/21-OT-AD2), which also funded Guillermo Marco's research.

Guillermo Marco's work was further supported by the Spanish government Ph.D. research grant (*Ministerio de Universidades*) FPU20/07321 and a scholarship of the Madrid City Council for the Residencia de Estudiantes (Course 2023–2024).

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A Formal Definition of the Evaluation Metrics

This appendix gives the exact formulae used for every metric reported in the paper. Throughout, let the evaluated text x consist of:

- S sentences $s_1, \dots, s_S$, where s_i has length (number of tokens) ℓ_i. Each sentence s_i can also be represented by a sentence-level embedding $\mathbf{e}_i \in \mathbb{R}^{d_e}$. The total number of tokens in x is $N = \sum \ell_i$.
- M equally sized word-sections $\sigma_1, \dots, \sigma_M$ (typically derived from x by splitting the token sequence) used for global coherence analysis. Each section σ_j is associated with a topic vector $\mathbf{t}_j \in \Delta^{K^\star - 1}$ derived from an LDA model with $K^\star$ topics.
- K fixed-length chunks $c_1, \dots, c_K$ (also derived from x by splitting the token sequence, possibly different from sections σ_j) used for affect analysis. Each chunk c_k has an associated sentiment score s_k and a dominant emotion D_k.
- E_j as the set of entities in sentence s_j, each entity $e \in E_j$ having a grammatical role $\mathrm{role}_j(e) \in \{S, O, X\}$ (Subject, Object, Other).

For stylistic analysis, $\mathcal{R}$ denotes the predefined set of rhetorical device types considered. For thematic analysis, C is the number of thematic clusters discovered from text segments, and p_c is the proportion of segments belonging to cluster c.

A.1 Coherence Metrics

Optimal number of topics ($K^\star$). To determine the optimal number of topics for LDA-based global coherence, we follow Röder et al. (2015) and select the topic count $K^\star$ that maximizes a topic coherence score, such as C_v:

$$K^\star = \arg \max_{K \in [K_{\min}, K_{\max}]} C_v(K). \tag{4}$$

This $K^\star$ is then used to generate topic vectors $\mathbf{t}_j$ for each section σ_j.

Entity–grid local coherence (C_{entity}). Adapting the entity-grid model of Barzilay and Lapata (2008), local coherence is assessed by measuring the continuity of entities and their grammatical roles across adjacent sentences:

$$C_{\text{entity}} = \frac{1}{S-1} \sum_{j=1}^{S-1} \frac{1}{|E_j \cup E_{j+1}|} \sum_{e \in E_j \cup E_{j+1}} \cdot \left[\mathbf{1}_{e \in E_j \cap E_{j+1}} + \tfrac{1}{2} \mathbf{1}_{\substack{e \in E_j \cap E_{j+1} \\ \mathrm{role}_j(e) = \mathrm{role}_{j+1}(e)}} \right]. \tag{5}$$

A higher C_{entity} suggests smoother transitions in entity focus.

Embedding-based local coherence (C_{local}). This metric, inspired by Li and Hovy (2014), quantifies local coherence as the average cosine similarity between the embeddings of adjacent sentences:

$$C_{\text{local}} = \frac{1}{S-1} \sum_{i=1}^{S-1} \cos(\mathbf{e}_i, \mathbf{e}_{i+1}). \tag{6}$$

Higher values indicate greater semantic similarity between consecutive sentences.

Global topic-vector coherence (C_{global}). Using section-level topic vectors $\mathbf{t}_j$ derived from an LDA model (Blei et al., 2003) with $K^\star$ topics, global coherence is the average cosine similarity across all pairs of section topic vectors:

$$C_{\text{global}} = \frac{2}{M(M-1)} \sum_{1 \le i < j \le M} \cos(\mathbf{t}_i, \mathbf{t}_j). \tag{7}$$

This captures the overall thematic consistency of the text.

A.2 Originality Metrics

Log-likelihood originality ($\mathrm{Orig}_{\mathbf{LL}}$). The originality of text x is assessed by its log-likelihood under a pre-trained left-to-right language model. Specifically, we utilize the `meta-llama/Llama-3.2-3B-Instruct` model from the Llama 3 family (AI at Meta, 2024). A higher score, as defined by Brown et al. (2020), indicates that the text is more predictable by the model, thus considered less original:

$$\mathrm{Orig}_{\mathrm{LL}}(x) = \sum_{n=1}^{N} \log p(w_n \mid w_{<n}), \tag{8}$$

where w_n is the n-th token and $w_{<n}$ are the preceding tokens.

A.3 Readability Metrics

SMOG Index. The SMOG grade, developed by McLaughlin (1969), estimates the years of education needed to comprehend a piece of text. It is calculated as:

$$\mathrm{SMOG} = 1.0430\sqrt{P \cdot \frac{30}{S_{\mathrm{SMOG}}}} + 3.1291, \tag{9}$$

where P is the count of polysyllabic words (words with 3 or more syllables) in a sample of 30 sentences, and S_{SMOG} is the number of sentences in that sample (typically 30, if available).

A.4 Sentiment Dynamics Metrics

These metrics analyze the emotional trajectory of the text using chunk-level sentiment scores s_k and dominant emotions D_k. Sentiment scores are derived using a fine-tuned RoBERTa-large model for sentiment analysis (Hartmann et al., 2023), while dominant emotions are identified using a RoBERTa-base model fine-tuned on the GoEmotions dataset (Demszky et al., 2020; Liu et al., 2019).

Average sentiment ($\bar{s}$) and Variance (σ_s^2). The overall sentiment tone and its consistency are captured by:

$$\begin{aligned} \bar{s} &= \frac{1}{K}\sum_{k=1}^{K} s_k, \\ \sigma_s^2 &= \frac{1}{K}\sum_{k=1}^{K}(s_k - \bar{s})^2. \end{aligned} \tag{10}$$

Emotional Volatility (Dominant Emotion Change, $V_{\text{emo-dom}}$). This measures the frequency with which the dominant emotion D_k changes between consecutive text chunks:

$$V_{\text{emo-dom}} = \frac{1}{K-1}\sum_{k=1}^{K-1} \mathbf{1}_{D_k \neq D_{k+1}}. \tag{11}$$

A higher value indicates more frequent shifts in the primary emotion conveyed.

A.5 Stylistic Features

A range of metrics capture stylistic variation and complexity.

Average sentence length (tokens, $\bar{\ell}$):

$$\bar{\ell} = \frac{1}{S}\sum_{i=1}^{S} \ell_i. \tag{12}$$

Average syntactic tree depth ($\bar{d}_{\text{syn}}$), following Lu (2010):

$$\bar{d}_{\text{syn}} = \frac{1}{S}\sum_{i=1}^{S} d_{\text{syn}}(s_i), \tag{13}$$

$$\tag{14}$$

where $d_{\text{syn}}(s_i)$ is the depth of the syntactic parse tree for sentence s_i.

Lexical Diversity (MTLD), by McCarthy and Jarvis (2010):

$$\mathrm{MTLD} = \frac{N}{Q_{0.72}}, \tag{15}$$

where N is total tokens and $Q_{0.72}$ is the number of text factors maintaining a Type-Token Ratio ≥ 0.72.

Maximum subordination depth ($d_{\text{sub-max}}$):

$$d_{\text{sub-max}} = \max_{i \in \{1,\ldots,S\}} \mathrm{sub\_depth}(s_i), \tag{16}$$

where $\mathrm{sub\_depth}(s_i)$ is the deepest level of clausal subordination within sentence s_i.

Sentence length standard deviation (σ_ℓ):

$$\sigma_\ell = \sqrt{\frac{1}{S}\sum_{i=1}^{S}(\ell_i - \bar{\ell})^2}. \tag{17}$$

Rhetorical device variety (V_{rhet}):

$$V_{\text{rhet}} = |\{r \in \mathcal{R} \mid \mathrm{count}(r, x) > 0\}|, \tag{18}$$

representing the number of unique types of rhetorical devices from set $\mathcal{R}$ detected in text x. The identification of specific devices, such as metaphors, leverages advanced language models (e.g., GPT-4o). This approach aligns with recent findings on the capabilities of Large Language Models for extracting metaphoric analogies, as explored by Boisson et al. (2025).

A.6 Thematic Structure Metrics

These metrics assess the organization and diversity of themes, derived from C thematic clusters found among text segments.

Thematic entropy (H_{themes}). Normalized entropy of the distribution of text segments across C themes, adapting Shannon's entropy (Shannon, 1948):

$$H_{\text{themes}} = -\frac{1}{\log C}\sum_{c=1}^{C} p_c \log p_c, \quad \text{for } C > 1. \tag{19}$$

$H_{\text{themes}} = 0$ if $C \leq 1$. p_c is the proportion of segments in theme c.

Thematic graph density (D_{graph}). Density of a graph where nodes are themes and edges represent inter-theme semantic similarity above a threshold, based on network theory (Newman, 2010):

$$D_{\text{graph}} = \frac{2E_{\text{th}}}{V_{\text{th}}(V_{\text{th}} - 1)}, \quad \text{for } V_{\text{th}} > 1. \tag{20}$$

$D_{\text{graph}} = 0$ if $V_{\text{th}} \leq 1$. V_{th} is the number of thematic clusters (nodes) and E_{th} is the number of edges.

Table 3: Mean Feature Values per Model/Author

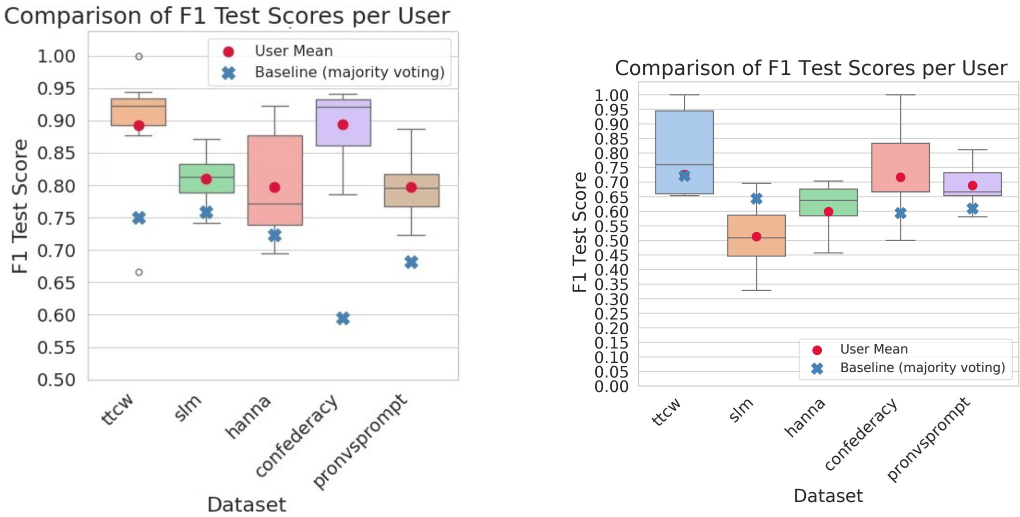
Dataset	Author	Topic count	Entity coh.	Local coh.	Global coh.	Log likelihood	SMOG	Mean sentiment	Emotional swings	Sentiment variance	Sentence length	Syntactic depth	MTLD	Max subord...	Rhetorical variety	Sentence rhythm	Topic entropy	Topic density
confederacy	Human	6.200	0.079	0.267	0.258	14323.5	8.120	-0.273	0.343	0.849	12.610	2.068	115.101	3.200	12.000	9.475	0.893	0.093
	alpaca	7.600	0.134	0.373	0.146	1961.4	10.900	0.928	0.507	0.100	21.967	2.012	-1102.454	1.600	3.800	3.330	0.325	0.200
	bard	6.600	0.104	0.384	0.276	8551.8	9.020	0.202	0.346	0.887	9.712	1.852	49.805	1.800	5.200	6.344	0.797	0.467
	bing	4.200	0.120	0.366	0.323	15107.5	8.760	-0.079	0.407	0.878	11.349	2.018	87.696	2.800	10.000	7.397	0.805	0.203
	chatgpt	4.700	0.037	0.336	0.327	13915.8	10.940	0.419	0.300	0.753	19.058	2.238	110.199	3	9.000	12.265	0.665	0.477
	claude12	5	0.033	0.314	0.358	6266.1	10.660	-0.049	0.243	0.876	15.158	2.045	199.570	2.400	9.000	10.270	0.573	0.167
	dolly	7.200	0.064	0.295	0.141	6801.5	9.520	-0.011	0.322	0.948	15.714	2.005	-250.798	2.800	7.000	10.442	0.863	0.176
	gpt4all	5.400	0.044	0.284	0.291	7222.5	9.180	0.779	0.365	0.361	18.661	2.112	75.783	2.800	6.800	11.693	0.606	0.400
	koala	7.400	0.050	0.387	0.223	7631.8	10.660	0.528	0.382	0.657	18.087	2.110	92.829	3	5.600	10.226	0.736	0.207
	oa	4.400	0.028	0.317	0.349	9177.3	10.340	0.575	0.344	0.567	17.092	2.159	-3363.100	3.200	7.400	11.562	0.863	0.279
	stablelm	5.800	0.056	0.377	0.266	5699.7	9.340	0.728	0.389	0.406	19.741	2.012	74.710	2.600	7.400	11.189	0.678	0.373
	vicuna	5.800	0.043	0.312	0.260	10636.3	9.680	0.587	0.362	0.599	17.911	2.102	72.796	2.800	7.200	11.065	0.722	0.293
hanna	Human	5.740	0.122	0.296	0.267	6960.7	7.008	-0.125	0.441	0.838	16.004	1.949	47.761	2.948	8.406	9.158	0.890	0.107
	bert	5.042	0.170	0.310	0.340	2747.2	6.326	-0.221	0.472	0.791	14.213	1.926	88.203	2.656	5.448	8.219	0.918	0.062
	ctrl	5.781	0.181	0.312	0.294	2554.5	6.014	-0.239	0.474	0.752	14.466	1.849	-282.722	2.677	2.802	9.036	0.918	0.059
	fusion	6.823	0.282	0.360	0.247	1629.3	5.071	-0.130	0.476	0.706	14.135	1.862	41.879	2.281	2.312	7.147	0.740	0.031
	gpt	5.833	0.165	0.296	0.306	2620.6	6.204	-0.191	0.484	0.832	13.345	1.897	-37.285	2.531	4.583	7.448	0.928	0.074
	gpt-2	4.865	0.174	0.302	0.349	4452.7	6.511	-0.157	0.497	0.839	13.343	1.888	79.343	2.792	6.729	7.563	0.902	0.077
	gpt-2-tag	4.948	0.160	0.306	0.337	4095.1	6.466	-0.122	0.488	0.802	14.577	1.936	80.103	2.948	5.865	8.072	0.903	0.095
	hint	5.698	0.567	0.510	0.383	1341.9	4.438	-0.133	0.405	0.548	11.824	1.883	21.624	1.469	2.031	6.403	0.374	0.038
	roberta	5.760	0.143	0.276	0.275	2569.8	6.578	-0.207	0.478	0.789	14.901	1.954	66.908	2.510	4.719	8.236	0.939	0.053
	td-vae	4.375	0.072	0.309	0.356	4268.4	6.819	-0.182	0.413	0.833	14.618	1.862	-825.543	3.021	5.260	9.857	0.927	0.091
	xlnet	5.146	0.224	0.302	0.356	3679.1	6.339	-0.038	0.430	0.844	14.145	1.967	50.383	2.667	3.385	8.071	0.838	0.180
pronvsprompt	Human	4.733	0.084	0.324	0.326	7452.0	12.967	0.054	0.283	0.908	34.585	2.513	110.984	3.300	7.983	24.497	0.883	0.092
	gpt4	4.383	0.038	0.476	0.359	10557.3	13.846	0.777	0.337	0.360	25.966	2.700	99.520	3.050	8.233	16.909	0.566	0.390
slm	Human	5.148	0.095	0.263	0.188	1059.5	6.307	0.222	0.260	0.621	24.996	2.239	-646.323	1.754	1.705	9.807	0.692	0.049
	bart-large	7.098	0.146	0.283	0.147	1113.8	3.803	0.555	0.286	0.478	28.223	2.846	-239.049	2.033	0.656	6.793	0.642	0.077
ttcw	Human	7.083	0.121	0.306	0.203	20185.0	7.575	-0.119	0.303	0.911	16.204	1.992	93.312	3.583	10.500	11.016	0.924	0.046
	claude	7.833	0.063	0.353	0.188	21671.3	8.950	0.300	0.498	0.815	16.386	2.190	132.927	3.333	9.833	9.095	0.741	0.183
	gpt3.5	8.500	0.048	0.414	0.179	33207.6	10.083	0.741	0.603	0.427	16.412	2.216	99.939	3.500	10.333	10.276	0.509	0.285
	gpt4	7.750	0.049	0.356	0.188	25545.2	10.658	0.225	0.356	0.891	21.918	2.336	130.641	3.417	11.000	15.114	0.729	0.142

Notation Summary. $\cos(\cdot,\cdot)$ denotes the cosine similarity. $\mathbf{1}_{\{\text{condition}\}}$ is an indicator function, equal to 1 if the condition is true, and 0 otherwise. All means and ratios are undefined (or typically set to 0 or NaN, as specified in context) if the denominator is zero. Δ^{k-1} is the $(k-1)$-simplex representing probability distributions over k categories. Unless specified (e.g., SMOG), S refers to the total number of sentences in text x. Logarithms are natural $(\ln)$ unless a base is specified (e.g., $\log_2$). For H_{themes}, the base of the log in the sum and in the normalization factor $1/\log C$ should be consistent (e.g., both natural log, or both base 2). Implementations often use natural log.

B Random Forest Model Performances and Metrics Correlation

This section addresses the validation of the selected metrics, models, and feature importances. Given the sensitivity of Random Forest feature importances with Gini entropy in distributing importance among correlated variables, we provide the Figure 5. This table demonstrates that none of the variables used to represent the texts and train the models exhibit correlations higher than 0.7.

Additionally, Figure 4 presents the visualization of F1 scores on the test set, illustrating the model's ability to predict preferences for previously unseen text pairs. Hyperparameters for both were tuned via grid search. For Logistic Regression, we explored $C \in \{0.01, 0.1, 1, 10\}$ with L1/L2 regularization. For Random Forest, parameters included $n\_estimators \in \{100, 200, 300\}$, $max\_depth \in \{None, 10, 20, 30\}$, $min\_samples\_split \in \{2, 5, 10\}$, $min\_samples\_leaf \in \{1, 2, 4\}$, and bootstrap/non-bootstrap sampling. Random Forest outperformed Logistic Regression, achieving higher F1 scores on the test set.



(a) F1 scores on test set - Random Forest

(b) F1 scores on test set - Logistic Regression

Figure 4: Comparison of F1 scores on test set for Random Forest and Logistic Regression. The boxplots illustrate the distribution of F1 scores across different datasets when modeling user preferences individually. The red dots indicate the mean F1 score for each user, while the blue crosses represent the performance of the baseline model trained on text pairs with majority voting consensus.

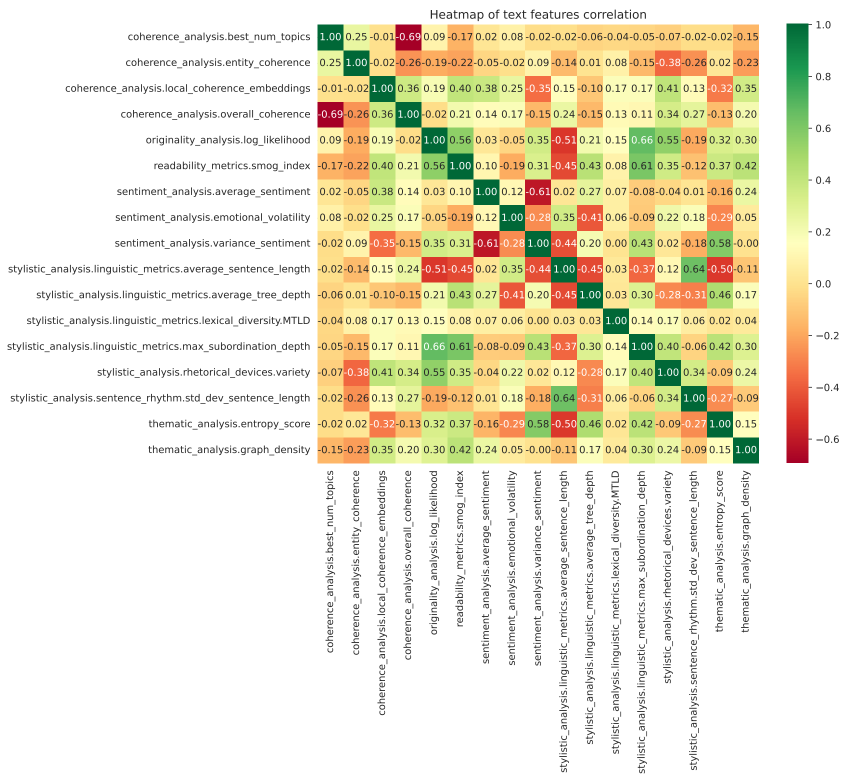


Figure 5: Correlation matrix of the textual features developed across all corpora. Notably, no highly positive or negative correlations are present, ensuring that feature importance is not skewed by redundancy in the Random Forest model.

C Dataset Profiles

C.1 Dataset Profile: SLM (Marco et al., 2025)

Text genre and format	Fictional movie synopses (approximately 80 words), written in response to a title. Half of the texts are human-written (collected and lightly edited from public film databases such as Wikipedia and TMDb), and the other half are generated by a fine-tuned BART-large model.
Genre homogeneity	All texts conform to the same narrative subgenre—short, single-paragraph movie synopses.
Corpus size	60 texts per condition (30 human-written and 30 AI-generated), evaluated under three experimental framings: (i) neutral (no authorship information), (ii) with explicit authorship labels, and (iii) deceptive framing (all texts labeled as AI regardless of source). In total, over 24,000 Likert-scale ratings were collected from human evaluators.
Annotator profile	68 master's students from an international business program. Participants had no formal literary training but were diverse in academic background and nationality. The sample is representative of a general, educated readership rather than literary experts.
Evaluation design	A between-subjects design was used: each participant rated only one synopsis per title, with balanced assignment to human or AI variants. The framing condition (authorship label) was randomized between participants. Texts were rated on multiple dimensions including creativity, informativeness, and overall quality. Two quiz variants were designed to balance exposure and ensure coverage.
Strengths	• Large number of ratings allows for robust statistical modeling of individual and aggregate preferences. • The use of framing conditions enables analysis of expectation bias in judgments of creativity. • Uniform text format enhances internal validity and minimizes stylistic confounds.
Limitations	• The genre is highly constrained (film synopses only), which may not reflect broader creative writing capabilities. • Human-written texts were not authored by professional writers and may not serve as high literary benchmarks. • All annotators were non-experts, potentially biasing evaluations toward surface-level qualities (e.g., clarity, coherence).
Observations	• AI-generated synopses outperformed human-written ones on most dimensions, except for creativity, where human texts had a slight edge. • Framing had a significant impact: revealing AI authorship led to lower ratings, while falsely labeling human texts as AI increased their perceived quality. • Creativity scores correlated strongly with informativeness, but not with attractiveness, suggesting distinct evaluative dimensions.

Table 4

C.2 Dataset Profile: Confederacy (Gómez-Rodríguez and Williams, 2023)

Text genre & format	65 short stories (250-1200 words) from a single prompt: "Write an epic narration of a single combat between Ignatius J. Reilly and a pterodactyl, in the style of John Kennedy Toole." 5 human-authored, 60 AI-generated (5 per model from 12 LLMs).
Genre homogeneity	Extremely high. All stories from the same prompt, targeting humor, epic structure, and Toole's style. Ensures comparability but limits generalization.
Corpus size	65 texts (5 human, 60 AI). Each rated by 2 independent raters on 10 dimensions (1300 ratings total), plus qualitative commentary. Each rater reviewed 13 texts.
Annotator profile	10 Honours/postgraduate Creative Writing students. Annotations blind to authorship.
Evaluation design	Stories rated 1-10 across 10 dimensions (e.g., plot, humor, style fidelity, originality, coherence). Implicit ranking. Annotators provided qualitative feedback.
Strengths	• Exceptional control over genre, topic, and style via unified prompt. • Evaluation rubric adapted from creative writing pedagogy. • Direct comparison of multiple SOTA LLMs and human performance. • Public availability of texts, annotations, and metadata.
Limitations	• Small human sample (5 stories), limiting human stylistic variation. • Only two annotators per story; moderate agreement ($k = 0.48$). • Highly specific task; results may not generalize broadly. • Some models (e.g., Bing) affected by prompt censorship, potentially skewing outputs.
Observations	• GPT-4 achieved highest mean scores, outperforming humans in most dimensions. • Humans retained a relative advantage in humor and originality. • Some models produced readable but stylistically flat stories. • LLMs excelled in formal aspects like epicness and structure.

Table 5

C.3 Dataset Profile: Pron vs Prompt (Marco et al., 2024)

Text genre & format	180 fictional film synopses (600 words each). 60 by human author Patricio Pron (Spanish). 120 by GPT-4: 60 using its own titles (30 ES, 30 EN) and 60 using Pron's titles (30 ES, 30 EN).
Genre homogeneity	High thematic/structural consistency (imaginary film synopses). Stylistic richness varies by title provenance and language, introducing controlled variation.
Corpus size	180 stories. 6 expert evaluators rated 120 stories each, yielding 7,200 judgments across creativity-related dimensions. Blind to authorship.
Annotator profile	Six literary experts (scholars, editors, instructors). Three assessed Spanish texts (GPT-4 + Pron); three bilingual experts assessed English GPT-4 texts vs. Spanish Pron texts.
Evaluation design	Rubric inspired by M. Boden's creativity dimensions (e.g., originality, narrative voice, attractiveness). Experts guessed authorship (human/AI) and gave qualitative comments. Blind evaluations.
Strengths	• First direct, controlled comparison between a world-class author and GPT-4. • Expert-driven rubric based on cognitive theory of creativity. • Cross-lingual setup reveals GPT-4 performance asymmetries by language. • Systematic manipulation of prompt provenance (human vs. AI titles) for co-authorship analysis.
Limitations	• Human texts from a single author (limits diversity). • Task-specific (synopses); may not generalize to other genres. • Expert-only evaluations; no general-audience reactions. • Potential influence of language asymmetry in bilingual expert comparisons. • Only one AI model (GPT-4) evaluated.
Observations	• GPT-4's performance significantly improved with human-authored titles (strong prompt sensitivity). • Experts' AI authorship detection improved over time (consistent GPT-4 stylistic signals). • GPT-4 performed better in English than Spanish across most dimensions. • GPT-4 rarely and inconsistently matched or surpassed the human author.

Table 6

C.4 Dataset Profile: TTCW (Chakrabarty et al., 2024)

Text genre & format	48 short stories (1000-2400 words), in 12 thematic quartets. Each: 1 *New Yorker* story (human), 3 AI-generated (GPT-3.5, GPT-4, Claude v1.3) from same one-sentence plot summary. Diverse themes/styles.
Genre homogeneity	All short fiction narratives from shared plot origin. Human texts are high-literary; AI attempts stylistic emulation. Ensures comparability, though human texts are from a narrow, high-end domain.
Corpus size	48 stories (12 human, 36 AI). Each evaluated by 3 experts using a 14-item binary rubric (adapted TTCT), yielding >2,000 creativity annotations.
Annotator profile	10 experts: creative writing professors, literary agents, MFA-trained writers. Each story assessed independently by 3 experts; provided comparative rankings and authorship guesses.
Evaluation design	Used adapted Torrance Test of Creative Writing (TTCW): 14 binary (yes/no) assessments in 4 dimensions (Fluency, Flexibility, Originality, Elaboration). Experts gave free-text commentary, rankings, blind authorship attribution.
Strengths	• First application of a structured creativity test (TTCT) to literary evaluation. • Balanced story lengths and aligned prompts enhance control. • High-quality expert judgments based on an established creativity framework. • Strong inter-rater reliability at aggregate level (Pearson $\rho = 0.69$).
Limitations	• Human texts are high-literary, potentially overstating AI–human gap. • No mid-tier/casual human writing; limited human stylistic diversity. • Evaluation process is time-consuming and hard to scale. • One-sentence plot conditioning may limit AI narrative divergence. • TTCW's binary rubric might not capture all nuances of creative quality.
Observations	• Human stories passed 84.7% of TTCW tests; GPT-4 27.9%, Claude v1.3 30.0%. • Experts ranked human stories as best in 89% of quartets. • Claude v1.3 was more often mistaken for human than GPT-based models. • Claude v1.3 performed best across Fluency, Flexibility, Elaboration; GPT-4 highest in Originality.

Table 7

C.5 Dataset Profile: HANNA (Chhun et al., 2022)

Text genre & format	1,056 stories generated by 10 different Automatic Story Generation (ASG) systems from 96 unique prompts (short sentences from WritingPrompts dataset). Each prompt is linked to a human-written reference story.
Genre homogeneity	High input homogeneity (short sentence prompts). Generated stories vary based on diverse prompts and system capabilities.
Corpus size	1,056 stories. Each annotated by 3 human raters (MTurk) on 6 criteria (19,008 annotations total). Includes scores from 72 automatic metrics.
Annotator profile	Amazon Mechanical Turk workers, filtered for English fluency, location (UK, US, CA, AU, NZ), and Masters Qualification.
Evaluation design	6 human criteria: Relevance (RE), Coherence (CH), Empathy (EM), Surprise (SU), Engagement (EG), Complexity (CX), rated on a 5-point Likert scale. Correlation analysis with 72 automatic metrics.
Strengths	• Comprehensive set of 6 orthogonal human evaluation criteria motivated by social sciences. • Large, publicly available dataset (HANNA) with human annotations and automatic scores. • Extensive meta-evaluation comparing 72 automatic metrics against human criteria. • Detailed inter-annotator agreement analysis (ICC2k reported).
Limitations	• Inter-annotator agreement is fair to moderate (ICC2k 0.29-0.56). • Annotators are MTurk workers, not literary experts. • Focused on stories generated from WritingPrompts; may not generalize to other ASG tasks/inputs. • Existing automatic metrics show weak correlation with human judgments, especially at story level.
Observations	• Human-written stories consistently score higher than AI-generated ones across all criteria. • Among ASG systems, GPT-2 (generic fine-tuned) performed best. • Automatic metrics correlate better with human judgments at system-level than story-level. • chrF and BARTScore are among the better performing automatic metrics, but human annotation is still advised.

Table 8