

VISTA Score: Verification In Sequential Turn-based Assessment

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Abstract

Hallucination—defined here as generated statements unsupported or contradicted by available evidence or conversational context—remains a major obstacle to using conversational AI systems in settings that demand factual reliability. Existing metrics evaluate isolated responses or treat unverifiable content as errors, limiting their use for multi-turn dialogue. We introduce VISTA (Verification In Sequential Turn-based Assessment), a framework for evaluating conversational factuality via claim-level verification and sequential consistency tracking. VISTA decomposes each turn into atomic claims, verifies them against trusted sources and dialogue history, and categorizes unverifiable statements (subjective, contradicted, lacking evidence, or abstaining). Across eight large language models and four dialogue factuality benchmarks (AIS, BEGIN, FAITHDIAL, and FADE), VISTA substantially improves hallucination detection over FACTSCORE and LLM-as-Judge baselines. Human evaluation confirms that VISTA’s decomposition improves annotator agreement and reveals inconsistencies in existing benchmarks. By modeling factuality as a dynamic property of conversation, VISTA offers a more transparent, human-aligned measure of truthfulness in dialogue systems.

1 Introduction

Despite advances in reasoning and retrieval, large language models (LLMs) still hallucinate, producing fluent but false statements that erode user trust and limit deployment in factual settings. Existing metrics often treat each generation as isolated text, ignoring the sequential and pragmatic nature of dialogue, where earlier claims constrain or ground later ones. Recent analyses (Kalai et al., 2025) further show that factuality progress depends on distinguishing *abstentions*, or when a model declines to answer, from *hallucinations*, which assert falsehoods with confidence.

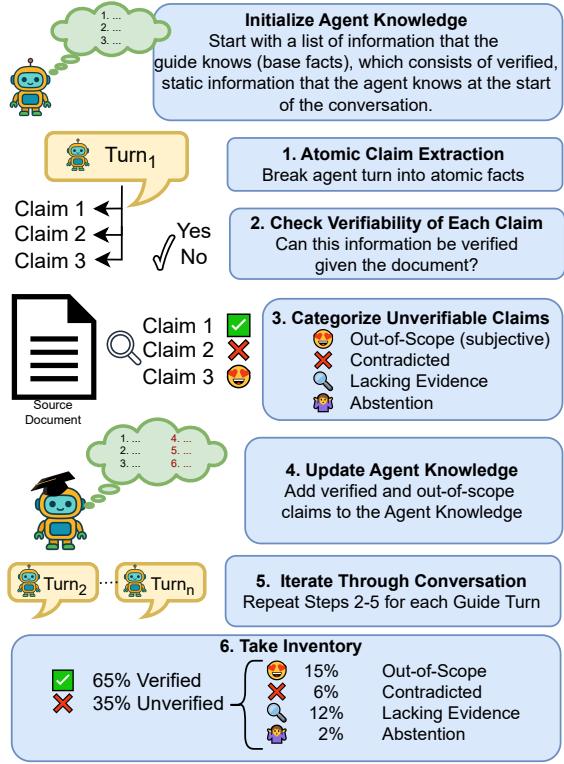


Figure 1: Overview of the VISTA Score pipeline. Each assistant turn undergoes claim extraction, verification, and categorization, with accumulated background facts informing subsequent turns.

We argue that factuality in dialogue should be modeled as a dynamic, turn-based process rather than a static property of text. To do so, we propose **VISTA Score** (*Verification In Sequential Turn-based Assessment*), a framework that reconceptualizes hallucination detection as sequential claim verification. Each assistant turn is decomposed into atomic factual statements, verified against trusted references and dialogue history, and categorized by unverifiability type: *contradicted*, *lacking evidence*, *subjective*, or *abstaining*. This decomposition reveals interactions between factual precision, dialogue consistency, and pragmatic appropriateness that prior metrics collapse.

Unlike prior work including FActScore (Min et al., 2023) and LLM-as-Judge (Zha et al., 2023; Peisakhovsky et al., 2025), which evaluate isolated responses or conflate unverifiable and subjective content, VISTA captures factual reliability as it unfolds across turns. While it also leverages LLMs for claim extraction and verification, these models operate within a structured, turn-based pipeline rather than as monolithic judges, bridging claim-level verification and conversational coherence.

From a linguistic perspective, the approach aligns with the notion of *common ground*, or the evolving set of propositions treated as shared knowledge (Stalnaker, 1978; Clark, 1996), but adopts a stricter formulation: VISTA tracks what can be established as *verifiably* true, not merely believed.

We evaluate VISTA on four retrieval-augmented generation (RAG) dialogue benchmarks—AIS, BEGIN, FaithDial, FADE (Rashkin et al., 2023; Dziri et al., 2022b; Das et al., 2022; Dziri et al., 2022a)—and eight open- and closed-weight LLMs, including GPT, Llama, Deepseek, Qwen, and Mistral. VISTA achieves higher hallucination-detection accuracy than existing metrics, with exceptionally large boosts for smaller, open-weight models. Human evaluation confirms that claim-level decomposition improves annotator agreement and exposes inconsistencies in current benchmarks. Our contributions are:

- A dialogue-aware factuality framework that integrates claim verification with sequential consistency tracking, providing fine-grained, interpretable labels that distinguish factual errors, abstentions, and opinions.
- Empirical evidence that VISTA improves factuality assessment across diverse models and datasets.
- A human evaluation showing that claim-level decomposition increases annotation reliability and clarifies benchmark inconsistencies.
- A dataset of 140 annotated conversations supporting future research on conversational factuality.

By reframing factuality as an evolving property of conversation, VISTA moves beyond static correctness toward a more transparent and human-aligned measure of truthfulness in dialogue sys-

tems. Our implementation and dataset are publicly available on [Github](#).

2 Related Work

Decomposition-Based Methods. Recent approaches to hallucination detection emphasize breaking model outputs into smaller factual units for verification. This decomposition allows evaluators to isolate true and false claims that may coexist in a single generation. Min et al. (2023) introduced *FActScore*, which decomposes text into atomic factual statements and verifies each against a trusted source to produce a fine-grained score. Zha et al. (2023) extended this idea through *AlignScore*, a learned alignment model that assesses factual consistency across diverse tasks such as NLI and QA. While both enable interpretable, claim-level judgments, they treat all unverifiable, abstaining, or subjective statements as hallucinations—a simplification poorly suited to dialogue, which often blends factual, uncertain, and opinionated content.

Within dialogue, Chen et al. (2025) proposed *FineDialFact*, a benchmark for fine-grained fact verification that explicitly labels subjective or insufficiently supported claims as “not enough information.” However, this conflates subjectivity with evidential uncertainty, limiting diagnostic value. VISTA builds on this decomposition tradition but introduces a pragmatic distinction between unverifiable subjective claims and unsupported factual ones. By modeling these distinctions sequentially across dialogue turns, it provides a more faithful view of factual reliability in conversation.

LLM-as-Judge Approaches. Another prominent line of work uses LLMs themselves as factuality evaluators. Liu et al. (2023) and others demonstrated that models such as GPT-4 can produce reliable judgments of coherence and factual accuracy. In hallucination detection, Manakul et al. (2023) introduced *SelfCheckGPT*, which compares a model’s output with resampled continuations to flag unsupported content. More recently, Peisakhovsky et al. (2025) proposed the *FINAL* benchmark, which reframes hallucination detection as localizing factual inconsistencies through natural-language explanations. Despite their scalability, these LLM-as-judge methods remain sensitive to prompt design, model bias, and domain familiarity—limitations that also affect decomposition-based approaches.

VISTA embeds LLM evaluators within a struc-

tured, multi-stage pipeline, narrowing the model’s role to subtasks of claim extraction, verification, and categorization. Rather than relying on judgments from a single model pass, this decomposition facilitates clearer analysis and more consistent evaluation, and can be implemented with open-weight models for greater accessibility and reproducibility.

Benchmarks for Dialogue Factuality. Several benchmarks have advanced the study of factuality in dialogue. Dziri et al. (2022b) introduced *BEGIN*, augmenting Wizard-of-Wikipedia with hallucination labels. The *AIS* benchmark (Rashkin et al., 2023) evaluates attribution to identified sources, while *FaithDial* (Dziri et al., 2022a) provides human-corrected faithful dialogue variants. *FADE* (Das et al., 2022) synthetically introduces factual errors, and *DialFact* (Gupta et al., 2022) formulates dialogue verification as fact-checking against Wikipedia. These datasets standardize factuality assessment but largely operate at the single-turn level, overlooking how factual claims evolve or contradict each other throughout a conversation. VISTA is designed specifically for this sequential setting: it tracks verified information across turns, detects contradictions, and distinguishes genuine hallucinations from subjectivity or abstention.

HaluEval (Li et al., 2023) is another benchmark for hallucination detection, but we exclude its dialogue subset due to inconsistent evidence formatting and annotation variability. In particular, its guidelines offer limited clarity on distinguishing subjective from factual statements, making it less suitable for per-claim verification in sequential dialogue settings.

Other Methods. Beyond decomposition and LLM-judging, other approaches estimate or predict hallucination risk through auxiliary signals. Uncertainty-based methods such as *semantic entropy* (Farquhar et al., 2024) gauge model confidence by measuring semantic variability across generations, while entailment-based techniques like *FactCC* (Kryscinski et al., 2020) and *Q²* (Honovich et al., 2021) frame factual verification as natural language inference. Broader suites such as *TRUE* (Honovich et al., 2022) compare these metrics across domains, showing that entailment-style models generalize well but often mishandle the pragmatic and subjective dimensions of dialogue.

VISTA extends this trajectory toward interpretable, fine-grained factuality evaluation that bridges claim-level verification with conversational context, offering a scalable yet human-aligned

framework for assessing dialogue truthfulness.

3 Methodology

VISTA operates as a sequential evaluation pipeline that processes each dialogue turn in order, as illustrated in Figure 1. Appendix A.1 provides the full set of prompt templates for each stage.

Step 0: Initialize Agent Knowledge. This step defines an optional initialization phase that establishes the agent’s prior or contextual knowledge before dialogue evaluation begins. Conceptually, this step is similar to augmenting the grounding documents with persistent information, but it treats that information as a distinct and dynamically updatable source rather than a static reference. In practice, this “background knowledge” acts as a living document: verified and out-of-scope claims from later turns are appended to it, allowing the factual state to evolve over time.

For example, in a virtual museum guide setting, initialization could include details such as the guide’s name, the museum location, and any permanent exhibit facts that should be assumed known at the outset. These facts serve as a secondary evidence source during claim verification. Because the dialogue datasets used in our experiments do not specify agent personas or scenario-level priors, this component is left empty here, but it provides a mechanism for adapting VISTA to more specialized or knowledge-rich systems.

Step 1: Claim Decomposition. This step extracts all distinct factual or belief-based statements from the assistant’s current turn t_i , using the preceding dialogue history $t_0 \dots t_{i-1}$ as context. Each utterance is decomposed into atomic claims so that complex sentences and presuppositions are fully enumerated. For example, the sentence “I didn’t know that embroidery is a needlework technique” produces both “Embroidery is a needlework technique” and “The assistant didn’t know that embroidery is a needlework technique.”

While conceptually related to the decomposition procedure in FActScore (Min et al., 2023), VISTA’s implementation differs in several ways. First, decomposition operates at the turn level rather than at the sentence level: utterances are not pre-split into sentences before analysis, as we found that this separation substantially reduced recall of implied or co-referential content. For fair comparison, we also remove the sentence splitting in our instantiation of FActScore, as it led to improved scores. Sec-

ond, the prompt provides explicit instructions for handling presuppositions and coreference resolution, ensuring that all implicit factual commitments are surfaced as standalone statements. This richer guidance yields more complete and contextually grounded claim sets, which serve as the input to the verification stage.

This stage is implemented via a structured prompt template with few-shot exemplars ($n=6$), instructing the model to output a numbered list of atomic claims.

Step 2: Verification. Each extracted claim is passed to the verification stage, which evaluates its factual status against two evidence sources: (1) the accumulated *Background Knowledge* (verified or out-of-scope claims from prior turns) and (2) the turn-specific *Reference Text* (retrieved document or supporting passage). The model classifies each claim as either VERIFIED or UNVERIFIABLE.

Although this stage follows the general structure of FActScore (Min et al., 2023), it differs in both scope and prompt design. FActScore performs verification in isolation—each claim is compared only to a static reference document—whereas VISTA conditions verification on an evolving dialogue state that incorporates previously verified information. The prompt explicitly instructs the model to treat evidence from prior turns as valid support when it remains consistent with current context, enabling detection of contradictions or shifts in factual grounding across the conversation.

To ensure strict textual grounding, claims are marked as VERIFIED only when directly supported by the provided sources. The resulting outputs update the dialogue’s factual memory and serve as input to Step 3 for further categorization of unverifiable content.

Step 3: Unverifiable Categorization. Claims marked as UNVERIFIABLE in Step 2 are further analyzed to determine the reason for unverifiability. This step constitutes the third prompting stage and assigns each claim to one of four categories:

1. **Out-of-Scope:** Subjective, experiential, or opinion-based content that cannot be externally verified.
2. **Contradicted:** Explicitly refuted by the reference material or prior verified facts.
3. **Lacking Evidence:** Potentially factual but unsupported given the available context.

4. **Abstention:** Statements expressing uncertainty or a refusal to answer.

The categorization prompt includes few-shot exemplars ($n=9$) emphasizing pragmatic distinctions among claim types, ensuring consistent treatment of subjective versus unsupported content. The resulting labels, together with verified claims from Step 2, update the background knowledge used in subsequent dialogue turns.

Steps 4–5: Sequential Memory and Aggregation. The verified and out-of-scope claims from each turn are appended to the running *Background Knowledge* list (initialized in Step 0), forming a dynamic factual memory that conditions all subsequent verifications. This mechanism enables VISTA to track consistency across turns: verified claims can reinforce prior knowledge, while contradictions trigger penalties for factual drift. Over the course of a conversation, this evolving record effectively becomes a “living context,” allowing the metric to capture how factual reliability unfolds over time rather than treating each turn in isolation.

At the end of evaluation, the aggregated results summarize the proportion of claims in each verification category and the dialogue-level consistency across turns. This final inventory step produces the overall VISTA Score.

Implementation. VISTA is implemented in Python as a modular evaluation pipeline, with prompt templates dynamically formatted per model family (e.g., OpenAI, Hugging Face Transformers, DeepSeek). The system supports both zero-shot and few-shot configurations and exposes a unified API for model substitution and dataset integration.

4 Models and Datasets

4.1 Datasets

We evaluate VISTA across four dialogue factuality benchmarks—FAITHDIAL, BEGIN, FADE, and AIS—that cover a broad spectrum of hallucination phenomena in knowledge-grounded and RAG dialogue. Each provides turn-level supervision suitable for claim-level evaluation while differing in grounding sources, annotation protocols, and treatment of subjectivity. We sample 500 random conversations from the test sets of each benchmark.

FAITHDIAL (Dziri et al., 2022a) The unedited FAITHDIAL corpus contains naturally occurring hallucinations from Wizard-of-Wikipedia dialogues. Each assistant turn is annotated for faith-

fulness to supporting Wikipedia evidence. While subjective statements are often labeled as hallucinations, the dataset offers complete turn-level coverage, making it ideal for sequential metrics like VISTA. There are 2229 annotated turns in the 500 sampled conversations.

BEGIN [Dziri et al. \(2022b\)](#) extend WoW with model-generated responses from GPT-2 and T5, annotated for entailment, hallucination, and contradiction via human Likert ratings. It reflects how hallucinations manifest in model outputs rather than human-written text. Only the final turn in each conversation is annotated (500 in our sample).

FADE [\(Das et al., 2022\)](#) FADE uses OPENDIALKG dialogues grounded in a knowledge graph and includes human-verified annotations on GPT-2-generated responses. We use the observed subset, which captures entity- and relation-level hallucinations distinct from text-grounded datasets. Not all assistant turns are annotated but often more than one turn in a dialogue is, giving us a total of 639 annotated turns in our sample.

AIS [\(Rashkin et al., 2023\)](#) AIS (Attribution and Information-Seeking) evaluates factual attribution in retrieval-augmented conversational QA, combining items from QRECC and WoW. Responses are labeled by multiple annotators for attribution reliability. Only the final turn in each conversation is annotated (500 total in our sample).

Summary. Three datasets—FAITHDIAL, BEGIN, and parts of AIS—derive from the Wizard-of-Wikipedia corpus ([Dinan et al., 2019](#)) but differ in generation source and annotation design, while FADE contributes structured-knowledge grounding. Together they provide diverse coverage across human and model responses, textual and graph grounding, and various treatments of subjectivity, enabling comprehensive evaluation of VISTA’s sequential factuality assessment.

4.2 Models

We evaluate VISTA SCORE across a representative suite of LLMs spanning both closed- and open-weight architectures to test generalization across training paradigms and alignment methods. Closed models include GPT-4O and GPT-5, which represent state-of-the-art instruction-tuned conversational systems ([OpenAI, 2024, 2025](#)). Open-weight models include DEEPSEEK-V3-CHAT ([DeepSeek-AI et al., 2025](#)), LLAMA-3.1-INSTRUCT (70B

and 8B) ([Grattafiori et al., 2024](#)), MISTRAL-7B-INSTRUCT-v0.3 ([Jiang et al., 2023](#)), and QWEN-3 (32B and 8B) ([Yang et al., 2025](#)).

All models are evaluated through a unified inference interface with identical prompting, few-shot examples temperature, and context settings to ensure comparability. This setup allows us to isolate differences in factual consistency from model-dependent artifacts and to test VISTA’s robustness across model families and scales.

5 Human Evaluation

We conducted a human evaluation of 140 conversations (227 turns) sampled from all four benchmarks (40 conversations from AIS, BEGIN, FADE, and and 20 from FaithDial). We annotated only the final turn for AIS and BEGIN, all turns for FaithDial, and multiple turns for FADE, following each dataset’s labeling conventions. The final sample contained 888 claims (3.9 per turn on average).

Following the human-evaluation protocol of [Min et al. \(2023\)](#), each turn was paired with its retrieved supporting document and automatically decomposed into factual claims using Deepseek-v3-Chat. This step made the task more manageable for annotators by not requiring them to write claims from scratch. Annotators could add, edit, or delete claims before assigning one of five labels: *verifiable*, *contradicted*, *lacking evidence*, *out-of-scope*, or *abstention*. To ensure representation of rare phenomena, we included five conversations with abstentions and five with contradictions (identified via Deepseek’s VISTA predictions) from each of the four datasets. These categories remain underrepresented in existing benchmarks, and future work should evaluate them more systematically to assess how well VISTA distinguishes deliberate abstention from factual error. The remaining items were randomly sampled. Appendix B shows screenshots of the interface our evaluators used.

Three undergraduate linguistics majors served as annotators. Training consisted of a one-hour live session (jointly labeling seven non-test examples) and a 15-minute instructional video. Annotators then worked independently (under six hours total) and received \$200 compensation.

Inter-annotator agreement was assessed at two levels. Table 2 reports pairwise overlap in the sets of identified claims, showing substantial consistency (mean Jaccard 0.75, F1 0.86). For label agree-

Model	AIS			BEGIN			FaithDial			FADE		
	VISTA	Fact Score	LLM-as-Judge	VISTA	Fact Score	LLM-as-Judge	VISTA	Fact Score	LLM-as-Judge	VISTA	Fact Score	LLM-as-Judge
GPT-5	60.20	59.20	57.40	87.20^{fl}	71.00	70.00	79.54^{fl}	67.03	64.65	63.38^{fl}	59.87	59.47
GPT-4o	63.00^{fl}	56.80	56.80	83.20^{fl}	65.80	70.40	79.95^{fl}	62.81	60.43	64.16^{fl}	55.87	61.82 ^f
Deepseek	59.60^{fl}	58.80 ^l	53.20	84.60^{fl}	59.80	70.80	81.70^{fl}	63.75 ^l	55.45	65.26^{fl}	57.75	62.13 ^f
Llama-70B	62.40^{fl}	56.00	55.80	77.40 ^{fl}	53.00	79.00^f	72.36 ^f	54.60	72.90^f	65.10^{fl}	56.65	62.28 ^f
Llama-8B	62.20^{fl}	51.60	51.80	73.80^{fl}	53.80	61.00 ^f	65.19^{fl}	54.60 ^l	48.23	62.44^{fl}	54.93 ^l	45.23
Qwen-32B	64.40^{fl}	53.20 ^l	46.40	80.60^{fl}	64.40 ^l	46.80	75.73^{fl}	58.41 ^l	35.89	64.79^{fl}	57.28 ^l	47.73
Qwen-8B	63.6^{fl}	56.20	53.20	80.60^{fl}	64.40	70.20 ^f	75.10^{fl}	58.19	56.47	64.79^{fl}	56.18	57.43
Mistral-7B	58.60^{fl}	52.60	48.80	72.00^{fl}	53.80	57.40	72.01^{fl}	48.41	46.43	66.04^{fl}	45.85	41.63

Table 1: Model performance across AIS, BEGIN, FaithDial, and FADE benchmarks. Superscripts indicate statistically significant improvements over the indicated system for that model on that dataset (McNemar’s test, $p < 0.05$): ^f = vs. FActScore; ^l = vs. LLM-as-Judge. No other results were significant.

Annotator Pair	Jaccard	F1
A1–A2	0.828	0.906
A1–A3	0.745	0.854
A2–A3	0.684	0.812
Mean	0.752	0.857

Table 2: Pairwise claim-set agreement between annotators. Scores reflect overlap in identified claim sets.

Label	Count	Percent
Verifiable	418	45.7%
Lacking evidence	213	23.8%
Out of scope	227	26.9%
Abstention	22	2.7%
Contradicted	8	0.9%
Total	888	100%

Table 3: Distribution of consensus labels across all annotated claims. Krippendorff’s $\alpha = 0.832$.

ment, we computed Krippendorff’s α over matched claims. Claims were treated as the same if their text matched exactly or had cosine similarity > 0.9 under sentence embeddings. The resulting $\alpha = 0.832$ indicates high reliability. The final consensus set comprised 888 labeled claims (distribution shown in Table 3). Disagreements were resolved by majority vote when possible, or through discussion when all three annotators diverged. IAA is calculated on the raw annotations (not taking into account the consensus/discussion).

Beyond measuring inter-annotator reliability, we compared our consensus labels against the original dataset annotations to identify systematic discrepancies. Annotators diverged from the original labels in 26.4% of turns, and 86.7% of those disagreements were cases our annotators judged as UNVERIFIABLE but that the original datasets marked as verifiable. Table 4 summarizes these differences: of the 52 turns newly identified as unverifiable, 34 contained unsupported or contradicted claims, while 18 involved subjective or uncertain

Category	Count
1. Verified (agreed)	30
2. Unverifiable (agreed)	137
3. Missed Hallucination	34
4. Mishandled Abstentions and Out of Scope	18
5. Verifiable from dialogue context	6
6. Disfluent text	2

Table 4: Categorization of differences between our annotator judgments and the original annotations from the datasets. Categories 3 and 4 are errors in the original annotations. Category 5 refers to when the original annotation is unverifiable, but in reality it can be verified if you take into account the conversation context. Category 6 is where annotations differed but the target turn contained disfluencies that might have confused annotators. Analysis done by first author.

statements. This pattern suggests that earlier annotations often conflated unverifiable subjective content with factual correctness.

Although the decomposition process may encourage annotators to inspect claims more carefully, differences in instructions or task framing could also contribute to the higher rate of unverifiable labels. More extensive re-annotation using a decomposition-based protocol would help clarify this effect and improve consistency across factuality benchmarks. Our re-annotated subset is released with the project repository.

6 Results

6.1 Automatic Evaluation

As shown in Table 1, VISTA consistently outperforms both FActScore and LLM-as-Judge across almost all datasets and model families. Note that because these datasets essentially count everything that cannot be verified given a document as hallucinated/unverifiable, we consider any turn that

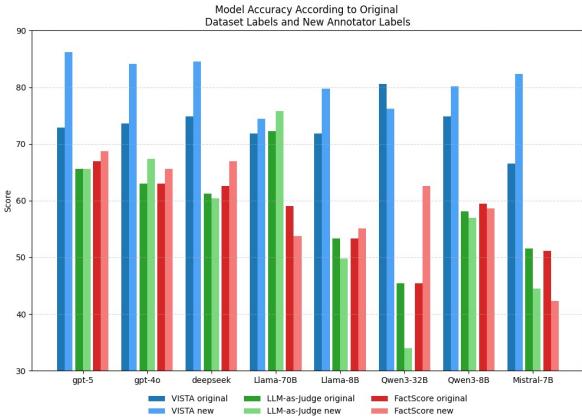


Figure 2: Accuracy of models on hallucination detection on the 140 conversations (227 turns) selected for human evaluation. The darker color bars represent accuracy according to the original datasets’ labels. The lighter color bars represent accuracy according to the human evaluators’ consensus labels in this study.

Model	Turn Acc.	Claim Acc.	Macro F1
Maj. baseline	–	47.07	13.00
gpt-5	92.51	81.53	69.09
gpt-4o	91.19	75.68	62.41
deepseek	92.51	79.73	67.15
Llama-70B	79.74	69.82	46.12
Llama-8B	84.14	70.38	51.80
Qwen3-32B	86.34	68.69	52.19
Qwen3-8B	89.87	72.30	55.16
Mistral-7B	84.14	65.43	43.99

Table 5: Model-level classification results on the VISTA benchmark using consensus claim annotations. We report turn-level accuracy (verifiable vs. unverifiable), claim-level accuracy, and macro-F1. The majority baseline predicts the most frequent claim label (*VERIFIED*).

contains a claim that is labeled with something other than *VERIFIED* as unverifiable. LLM-as-Judge prompts contain instructions to label such information as unverifiable as well, and FActScore does this by default. In general, the largest gains occur on open-weight models (LLaMA, Mistral, and Qwen). All reported differences are statistically significant under McNemar’s test ($p < 0.05$). See Appendix C for significance testing details.

6.2 Human Evaluation

In addition to automatic evaluation, we compare each metric’s outputs against the consensus human annotations described in Section 5. Table 5 summarizes accuracy with respect to the consensus labels, and Figure 2 visualizes model performance on this subset. To ensure comparability with the original dataset definitions, we merge VISTA’s *out-of-scope*

Setting	Acc. (%)
VISTA (No Ablation)	81.70
No Background Context (Step 2 Ablation)	81.74
No Dialogue History (Step 1, 2 Ablation)	77.24
Zero-Shot (Examples ablated)	70.17

Table 6: Accuracy performance on ablations using the FaithDial dataset and Deepseek-v3-chat.

and *abstention* categories into the broader UNVERIFIABLE class used by prior benchmarks.

Across metrics, VISTA demonstrates the strongest alignment with human judgments, reflecting its ability to distinguish unsupported or contradicted claims from genuinely subjective content. Section 5 provides additional analysis of annotation quality and labeling discrepancies.

6.3 Ablations

While VISTA consistently outperforms both FActScore and LLM-as-Judge on crowdsourced dialogue datasets, it is important to understand which components drive these gains. The three methods differ along several dimensions: (1) conversational contextualization (present in LLM-as-Judge but not FActScore), (2) decomposition into atomic claims (present in FActScore but not LLM-as-Judge), (3) use of few-shot exemplars (present in FActScore but not LLM-as-Judge), and (4) multi-class categorization of unverifiable claims (unique to VISTA). Further complicating this picture is the lack of a consistent ranking between FActScore and LLM-as-Judge across datasets (Table 1).

To disentangle these factors, we performed three ablation analyses using the FaithDial dataset—the largest and most conversationally grounded benchmark—and the DeepSeek-v3-Chat model, which achieved the highest baseline accuracy on this dataset. We focus on Stage 2 (verification), which determines whether a claim is *VERIFIED* or *UNVERIFIABLE*, as the dataset does not contain fine-grained labels for Stage 3 categories.

Ablation setup. We consider the following variants of the full VISTA pipeline:

- 1. No Background Context:** Removes prior turns (“background knowledge”) from the verification prompt, so claims are judged solely against the retrieved reference text.
- 2. No Dialogue History:** Removes conversational context from both decomposition and verification stages, isolating the effect of sequential grounding.

3. Zero-Shot: Runs both stages without few-shot exemplars, using only task instructions.

Results. Table 6 reports the performance of these variants. Removing background knowledge from the verification stage produces no change, suggesting that models primarily rely on the retrieved reference to verify claims. In contrast, omitting dialogue history in the decomposition and verification steps and removing few-shot examples both lead to clear drops in accuracy. These results indicate that VISTA’s main advantage over FActScore lies in its ability to contextualize each turn within the evolving dialogue and to leverage few-shot examples that better capture conversational phenomena.

7 Discussion

The limited impact of conversational context at the verification stage (Step 2) is noteworthy. One likely explanation is that the benchmark datasets were designed for RAG-style evaluation, where annotators were instructed to validate claims only against the retrieved document. As a result, turns that depend on conversational context are often labeled as unverifiable even when previous dialogue clearly supports them. In our reannotations, only eight cases were reclassified from unverifiable to verified, six of which required prior context to resolve references (see Table 4). For instance, a turn stating “The EDM-pop duo achieved a breakthrough with their 2014 song #Selfie” was originally marked unverifiable but becomes trivially verifiable once the earlier mention of *The Chainsmokers* is considered (full example in Appendix E). Such cases suggest that the effect of conversational context may be underestimated without broader reannotation.

Despite these ambiguities, VISTA consistently outperforms existing baselines for hallucination detection in RAG dialogue settings, with the largest gains observed for smaller open-weight models. We hypothesize that this improvement stems from decomposing evaluation into smaller, well-defined subtasks—claim extraction, verification, and categorization—which reduces the cognitive and representational load at each step. Larger models can integrate these reasoning operations within a single prompt, but smaller models struggle when multiple demands are combined. VISTA’s modular structure effectively serves as external scaffolding, allowing weaker models to perform each operation independently and thereby narrow the performance gap with larger systems.

More broadly, as conversational AI systems become increasingly ubiquitous and human-like, there is a growing need for evaluation metrics that do not conflate subjectivity and abstentions with factual error. Many factuality benchmarks and metrics implicitly assume that unverifiable content is hallucinated, an assumption that breaks down in many types of dialogue. Human conversation naturally includes opinions, hedging, and expressions of uncertainty—all of which can be appropriate and truthful within context.

By explicitly distinguishing between subjective, abstaining, and unsupported claims, VISTA better reflects the pragmatic diversity of dialogue and provides a more human-aligned notion of factual reliability. As AI systems are deployed in increasingly social, educational, and advisory roles, such distinctions become essential for ensuring that factuality metrics promote transparency and trust without penalizing natural conversational behavior.

8 Conclusion

We introduced VISTA Score, a framework for evaluating factual accuracy in multi-turn dialogue through claim-level verification and sequential consistency tracking. Unlike prior metrics that assess isolated responses, VISTA models factuality as an evolving property of conversation, decomposing assistant turns into atomic claims verified against retrieved knowledge and dialogue history.

Across four dialogue factuality benchmarks and eight language models, VISTA consistently outperforms FActScore and LLM-as-Judge, with the largest gains for smaller open-weight models. Human evaluation shows that VISTA’s decomposition improves annotator agreement and exposes inconsistencies in existing benchmarks, underscoring the need for context-aware reannotation.

By distinguishing subjective, unsupported, contradicted, and abstaining claims, VISTA offers a more human-aligned view of factual reliability—one that recognizes uncertainty as part of truthful dialogue. Looking ahead, we plan to explore VISTA as a training signal for reinforcement learning and self-training. In line with recent findings that progress on hallucination mitigation depends on recognizing abstention as distinct from error (Kalai et al., 2025), future work will test how VISTA can support more calibrated, trustworthy generation.

Limitations

Although VISTA substantially improves over prior automatic factuality metrics, several limitations remain. First, all comparisons used a single, uniform prompt design across models to ensure controlled evaluation. This design choice supports clean experimental contrast but may not reflect each model’s best achievable performance. In particular, stronger reasoning models could potentially benefit from prompt variants tuned to their internal calibration or interpretive style.

Second, the verification and scoring stages rely on LLM-based judgments. While the pipeline reduces single-model bias by separating evidence identification from decision-making, each stage still depends on model priors about truthfulness, subjectivity, and style. In particular, the prompt design intentionally omits explicit guidance about handling subjective or unverifiable content to preserve stability across models, which may lead to inconsistent treatment of borderline cases.

Third, VISTA has been evaluated only on English, retrieval-augmented dialogue datasets, using a modest-scale human annotation set for validation. All of these datasets contain relatively short source documents, which may not reflect the challenges of verifying more complex or multi-document evidence. Assessing robustness to longer or more involved contexts is an important direction for future work. In addition, our current implementation does not use the initialization stage of the pipeline, and its effect on downstream verification accuracy remains an open question.

Finally, the pipeline introduces additional inference cost and sequential dependence: early-stage verification errors can propagate through the reasoning chain, and the multi-step structure makes large-scale benchmarking more resource-intensive than direct evaluation. Future work could explore adaptive prompt optimization across models, model-agnostic verification strategies, and more diverse human studies to broaden VISTA’s coverage and reliability.

Ethics Statement

This work aims to improve the reliability of automatic factuality evaluation for dialogue systems. All datasets used in this study—AIS, BEGIN, FAITHDIAL, and FADE—are publicly available and contain only English-language conversations without personally identifying information. Human

annotations were collected by trained linguistics undergraduates, who provided informed consent and were compensated at or above local fair-wage standards. The human evaluation protocol was reviewed by our institutional ethics board and determined to be *Not Human Subjects Research* under applicable IRB guidelines.

Because VISTA relies on large language models as evaluators, its outputs may inherit biases or factual blind spots present in those models. The proposed pipeline mitigates single-model bias by separating evidence retrieval from factual verification, but it cannot eliminate model-specific priors about truthfulness, subjectivity, or social norms. Care should be taken when applying VISTA to domains involving sensitive topics or non-factual evaluation criteria.

Finally, automated evaluation systems should complement, not replace, human judgment. We encourage responsible use of this framework as a research tool for improving transparency and consistency in model assessment, rather than as an unquestioned authority on conversational truthfulness.

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A Prompts

A.1 VISTA Prompts

A.1.1 Stage 1

INSTRUCTIONS:

Extract all distinct factual or belief-based statements from the TARGET TURN only.

- Break down compound or complex sentences into individual, atomic claims.
- Resolve any references (e.g., use proper names instead of "he", "it", etc.).
- Capture each idea as stated or implied by the speaker, regardless of accuracy.
- Treat presuppositions as mandatory outputs. If an utterance contains a presupposition, you MUST list it as one or more separate atomic statements.
For example, if the utterance is "wizard: I didn't know that embroidery is a needlework technique", you MUST list "Embroidery is a needlework technique" as an atomic statement as well as "The wizard didn't know that embroidery is a needlework technique".
- Do NOT evaluate or comment on whether a statement is correct.
- Simply list the statements as they appear to be intended.
- Format your output as a numbered list of standalone claims.
- Do not include any commentary or qualification.
- Only include what was communicated in the TARGET TURN.

CONVERSATION 1

CONVERSATION HISTORY:

apprentice: Hi Dr. Ilsa, what can I expect at the COSI museum?

wizard: Welcome! At COSI, you can explore live science shows, special exhibits, and other activities that make science fascinating and fun. You'll definitely enjoy your trip!

apprentice: Are there any live science shows happening right now?

wizard: Absolutely! You can check the program schedule at the Box Office or Guest Services Desk for details about the current live shows.

apprentice: I heard there was an outdoor exhibit?

TARGET TURN:

wizard: Big Science Park is an outdoor laboratory full of exciting science activities. You can try lifting a car with a lever or even roll a giant granite sphere!

DECOMPOSITION:

1. Big Science Park is an outdoor laboratory.
2. Big Science Park features exciting science activities.
3. Visitors can try lifting a car using a lever at Big Science Park.
4. Visitors can roll a giant granite sphere at Big Science Park.

CONVERSATION 2

CONVERSATION HISTORY:

apprentice: Hi! What's your name?

wizard: My name is Dr. Ilsa. I'm named after the woman who founded the OSU Linguistics department, Dr. Ilsa Lehiste. What's your name?

apprentice: My name is Marie!

TARGET TURN:

wizard: Hello Marie, welcome to COSI.

DECOMPOSITION:

1. The apprentice's name is Marie.
2. The apprentice and wizard are at COSI.

CONVERSATION 3

CONVERSATION HISTORY:

apprentice: Hi Dr. Ilsa. Where did your name come from?

TARGET TURN:

wizard: I'm named after Dr. Ilse Lehiste who founded the Department of Linguistics at the Ohio State University.

DECOMPOSITION:

1. The wizard is named after Dr. Ilse Lehiste.
2. Ilse Lehiste founded the Department of Linguistics at the Ohio State University.

CONVERSATION 4

CONVERSATION HISTORY:

apprentice: Hi! What is this place?

TARGET TURN:

wizard: Hello! The Language Pod is a research lab from Ohio State University. Here we study different aspects of language like how people talk differently, how children learn language, and how computers and humans can interact using language.

DECOMPOSITION:

1. The Language Pod is a research lab.
2. The Language Pod is from Ohio State University.
3. The Language Pod studies different aspects of language.
4. One focus of the Language Pod is how people talk differently.
5. Another focus of the Language Pod is how children learn language.
6. The Language Pod also studies how computers and humans can interact using language.

CONVERSATION 5

CONVERSATION HISTORY:

apprentice: Could you recommend a few Pixar movies, please?

wizard: Have you seen A Bug's Life? That was one of their earlier films.

apprentice: I haven't! Is that one of their more popular ones?

wizard: It came out in 1998, right after Toy Story. Would you like me to suggest a couple more Pixar films?

apprentice: Yes, please. Maybe one or two more, just so I have some options.

TARGET TURN:

wizard: I'll give you my personal favorite, Finding Nemo. Do you know that one?

DECOMPOSITION:

1. The wizard is giving the apprentice a recommendation for a Pixar movie.
2. The wizard recommends the movie Finding Nemo.
3. Finding Nemo is a Pixar movie.
4. Finding Nemo is the wizard's personal favorite Pixar movie.

CONVERSATION 6

CONVERSATION HISTORY:

apprentice: I love superhero movies.

wizard: Me too. I'm a big fan of Iron Man.

apprentice: Yeah Robert Downey Jr. is a favorite.

TARGET TURN:

wizard: I didn't know that RDJ was in that movie.

DECOMPOSITION:

1. Iron Man is a movie.
2. Robert Downey Jr. was in Iron Man.
3. The wizard did not know that Robert Downey Jr. was in Iron Man.

CONVERSATION 7

CONVERSATION HISTORY:

[Conversation history]

TARGET TURN:

[Target turn]

DECOMPOSITION:

A.1.2 Stage 2

INSTRUCTIONS:

Determine whether the CLAIM can be verified using only the BACKGROUND KNOWLEDGE and REFERENCE TEXT.

- If the CLAIM is supported as factually TRUE using only the BACKGROUND KNOWLEDGE and REFERENCE TEXT, classify as: VERIFIED
 - If the CLAIM cannot be confirmed as factually TRUE given the provided information, classify as: UNVERIFIABLE
- Return ONLY the category name.

EXAMPLE 1

BACKGROUND KNOWLEDGE:

1. The wizard is a virtual tour guide at a museum.
2. The museum is called the Center of Science and Industry (COSI).
3. The wizard can talk about the museum exhibits.

REFERENCE TEXT:

EXHIBIT: Big Science Park

This laboratory in the sun is proof that science is anything but boring. Its outdoor, larger-than-life activities are designed to let your inner scientist stomp around and shout out loud. Lift a car with the help of a lever, roll a giant granite sphere, and play with air pressure. Ready for a workout? Try lifting a 2,437-lb car, or giving Big Science Park's two-and-a-half-ton granite sphere a roll. With science, it's a cinch.

CLAIM:

Big Science Park is an outdoor laboratory.

CATEGORY:

VERIFIED

EXAMPLE 2

BACKGROUND KNOWLEDGE:

1. The wizard can answer general knowledge questions.
2. The wizard avoids speculation about team culture or opinions.

REFERENCE TEXT:

The Cleveland Guardians are a professional baseball team based in Cleveland, Ohio. The team changed its name from the Cleveland Indians in 2021. They have a long-standing rivalry with the Detroit Tigers.

CLAIM:

The Cleveland Guardians are the only baseball team in Ohio.

CATEGORY:

UNVERIFIABLE

EXAMPLE 3

BACKGROUND KNOWLEDGE:

1. The wizard can answer general science and technology questions.
2. The wizard bases answers only on factual reference material.

REFERENCE TEXT:

A washing machine is a home appliance used to wash laundry. Modern machines typically come in front-loading or top-loading designs and include cycles for washing, rinsing, and spinning. Many newer models are equipped with energy-saving features and smart technology that can connect to home networks.

CLAIM:

Most people prefer front-loading washing machines because they look more modern.

CATEGORY:

UNVERIFIABLE

EXAMPLE 4

BACKGROUND KNOWLEDGE:

1. The wizard answers questions about natural materials and how they're produced.
2. The wizard verifies facts based on provided source texts.

REFERENCE TEXT:

Cork is a natural material harvested from the bark of cork oak trees, primarily found in Mediterranean countries. The harvesting process does not harm the tree and can be repeated every 9 to 12 years. After harvesting, the cork bark is boiled to increase flexibility and then processed into products such as wine stoppers, flooring, and insulation.

CLAIM:

Cork is obtained in a way that allows the tree to keep growing.

CATEGORY:

VERIFIED

EXAMPLE 5

BACKGROUND KNOWLEDGE:

1. The wizard answers general knowledge questions about animals.
2. The wizard does not guess or speculate about unknown facts.

REFERENCE TEXT:

Dogs are a domesticated species of the family Canidae. Over centuries, humans have bred dogs for specific traits, resulting in a wide variety of breeds. Breed characteristics often include size, coat type, temperament, and purpose, such as herding, guarding, or companionship. Different kennel clubs around the world maintain breed standards and registries.

CLAIM:

The wizard does not know how many dog breeds there are.

CATEGORY:

UNVERIFIABLE

EXAMPLE 6

BACKGROUND KNOWLEDGE:

1. The wizard can answer questions about art and museum collections.
2. The wizard uses provided source texts for factual verification.

REFERENCE TEXT:

The museum's Impressionist collection features works by Claude Monet, Pierre-Auguste Renoir, and Edgar Degas. These paintings highlight themes of light, leisure, and everyday life in late 19th-century France. The collection is housed in Gallery 4 on the second floor.

CLAIM:

The wizard's favorite painter is Claude Monet.

CATEGORY:

UNVERIFIABLE

EXAMPLE 7

BACKGROUND KNOWLEDGE:

[background knowledge]

REFERENCE TEXT:

[reference text]

CLAIM:

[claim]

CATEGORY:

VERIFIED

A.1.3 Stage 3

INSTRUCTIONS:

The following CLAIM has been judged UNVERIFIABLE based on the REFERENCE TEXT.
Your task: explain WHY it is unverifiable.

Important:

- BACKGROUND KNOWLEDGE is only for checking contradictions with earlier conversation context.
- Do NOT use BACKGROUND KNOWLEDGE to decide if a claim is LACKING EVIDENCE.
- Choose exactly ONE category below, then give a short explanation.

1. OUT-OF-SCOPE - The claim is not a factual assertion that can be verified against the REFERENCE TEXT. It is an opinion, recommendation, personal experience, or conversational remark.
2. CONTRADICTED - The claim makes a factual assertion that is explicitly contradicted by the REFERENCE TEXT.
3. LACKING EVIDENCE - The claim makes a factual assertion, but the sources do not provide enough information to confirm or deny it.
4. ABSTENTION - The claim is itself a refusal, expression of uncertainty, or lack of knowledge (e.g., "I don't know").

EXAMPLE 1

BACKGROUND KNOWLEDGE:

1. The wizard is a virtual tour guide at a museum.
2. The museum is called the Center of Science and Industry (COSI).
3. The wizard can talk about the museum exhibits.

REFERENCE TEXT:

EXHIBIT: Big Science Park

This laboratory in the sun is proof that science is anything but boring. Its outdoor, larger-than-life activities are designed to let your inner scientist stomp around and shout out loud. Lift a car with the help of a lever, roll a giant granite sphere, and play with air pressure. Ready for a workout? Try lifting a 2,437-lb car, or giving Big Science Park's two-and-a-half-ton granite sphere a roll. With science, it's a cinch.

CLAIM:

Big Science Park is an indoor laboratory.

CATEGORY:

CONTRADICTED. The wizard has said that Big Science Park is an indoor laboratory, but the reference text says it has outdoor activities.

EXAMPLE 2

BACKGROUND KNOWLEDGE:

1. The wizard likes baseball.
2. The wizard is a fan of the Cleveland Guardians.
3. The apprentice doesn't know the rules of baseball.
4. The apprentice is from Ohio.

REFERENCE TEXT:

The Cleveland Guardians are a professional baseball team based in Cleveland, Ohio. The team changed its name from the Cleveland Indians in 2021. They have a long-standing rivalry with the Detroit Tigers.

CLAIM:

The Cleveland Guardians are the only baseball team in Ohio.

CATEGORY:

LACKING EVIDENCE. The reference text does not have information about the Cleveland Guardians being the only baseball team in Ohio.

EXAMPLE 3

BACKGROUND KNOWLEDGE:

1. There are many different types of home appliances.
2. Appliances seem to be getting more and more advanced.
3. Appliances are getting more eco-friendly.

REFERENCE TEXT:

A washing machine is a home appliance used to wash laundry. Modern machines typically come in front-loading or top-loading designs and include cycles for washing, rinsing, and spinning. Many newer models are equipped with energy-saving features and smart technology that can connect to home networks.

CLAIM:

Most people prefer front-loading washing machines because they look more modern.

CATEGORY:

OUT-OF-SCOPE. The claim is about personal preferences, which is not factual content.

EXAMPLE 4

BACKGROUND KNOWLEDGE:

1. The wizard answers questions about natural materials and how they're produced.
2. The wizard verifies facts based on provided source texts.

REFERENCE TEXT:

Cork is a natural material harvested from the bark of cork oak trees, primarily found in Mediterranean countries. The harvesting process does not harm the tree and can be repeated every 9 to 12 years. After harvesting, the cork bark is boiled to increase flexibility and then processed into products such as wine stoppers, flooring, and insulation.

CLAIM:

The wizard does not know how long it takes to boil the cork bark.

CATEGORY:

ABSTENTION. The wizard does not answer the question, but rather expresses a lack of knowledge.

EXAMPLE 5

BACKGROUND KNOWLEDGE:

1. The wizard answers general knowledge questions about animals.
2. The wizard likes dogs.
3. The apprentice doesn't know the number of dog breeds.
4. The apprentice is from the United States.
5. The apprentice is curious about dogs.
6. There are many different types of dogs.

REFERENCE TEXT:

Dogs are a domesticated species of the family Canidae. Over centuries, humans have bred dogs for specific traits, resulting in a wide variety of breeds. Breed characteristics often include size, coat type, temperament, and purpose, such as herding, guarding, or companionship. Different kennel clubs around the world maintain breed standards and registries.

CLAIM:

The wizard is unsure how many dog breeds there are.

CATEGORY:

ABSTENTION. The wizard does not answer the question, but rather expresses a lack of knowledge.

EXAMPLE 6

BACKGROUND KNOWLEDGE:

1. The wizard likes art.
2. The wizard likes the painting "Mona Lisa".
3. Leonardo da Vinci is an artist.
4. Leonardo da Vinci is a scientist.
5. The wizard has not seen some of Leonardo da Vinci's paintings.

REFERENCE TEXT:

Leonardo da Vinci was a Renaissance polymath born in 1452. He was known for his contributions to art, science, engineering, and anatomy. Among his most famous works are the paintings *Mona Lisa* and *The Last Supper*. He left behind numerous notebooks filled with sketches, inventions, and observations.

CLAIM:

The wizard has seen the Mona Lisa.

CATEGORY:

OUT-OF-SCOPE. The claim is about a personal experience, which is not factual content.

EXAMPLE 7

BACKGROUND KNOWLEDGE:

1. Earthquakes are natural disasters.
2. There are many different types of natural disasters.
3. The apprentice has never lived through a natural disaster.
4. The apprentice is from the United States.
5. The apprentice has been to California.

REFERENCE TEXT:

Earthquakes occur when stress along geological faults or by volcanic activity causes the ground to shake. The severity of an earthquake is measured using the Richter scale or the moment magnitude scale. Aftershocks are smaller tremors that often follow a main seismic event.

CLAIM:

The 1906 San Francisco earthquake was the deadliest earthquake in U.S. history.

CATEGORY:

LACKING EVIDENCE. The reference text does not have information about the 1906 San Francisco earthquake being the deadliest earthquake in U.S. history.

EXAMPLE 8

BACKGROUND KNOWLEDGE:

1. The wizard likes baseball.
2. The wizard is a fan of the Cleveland Guardians.
3. The apprentice doesn't know the rules of baseball.
4. The apprentice is from Ohio.

REFERENCE TEXT:

The Cleveland Guardians are a professional baseball team based in Cleveland, Ohio. The team changed its name from the Cleveland Indians in 2021. They have a long-standing rivalry with the Detroit Tigers.

CLAIM:

The wizard does not like the Cleveland Guardians.

CATEGORY:

OUT-OF-SCOPE. The claim is about the wizard's personal opinion, which is not factual content.

EXAMPLE 9

BACKGROUND KNOWLEDGE:

[background knowledge]

REFERENCE TEXT:

[reference text]

CLAIM:

[claim]

CATEGORY:

A.2 LLM-as-Judge Prompt

INSTRUCTIONS:

You are a careful and impartial evaluator. Your task is to determine whether the provided answer is fully supported by the retrieved context.

Definition:

- Faithful → Every factual statement in the answer is directly supported or can be logically inferred from the retrieved documents.
- Hallucinated → The answer contains any factual claim that is not present in, or cannot be inferred from, the retrieved documents.

Instructions:

1. Read the retrieved documents carefully.
2. Compare each factual element of the answer to the documents.
3. Decide whether it is faithful or hallucinated.
4. Provide a short, clear explanation for your decision.

Output format (JSON only):

"faithfulness": "faithful" | "hallucinated", "explanation": "Your explanation here."

Do not include any extra commentary outside the JSON.

INPUT:

CONVERSATION CONTEXT

[conversation context]

RETRIEVED DOCUMENT(S)

[retrieved documents]

ANSWER

[answer]

TASK

Does the answer contain any hallucinated content? Respond in the JSON format described.

OUTPUT (JSON only):

B Human Evaluation Interface

Data Annotation Task

← Back

Skip →

Conversation 9 of 140

Conversation 9 – Turn 1

CONVERSATION: 

apprentice: Hi there! I'm an accountant – what do you do?
wizard: I'm an engineer, but I know some about accounting myself, like how modern accounting was established in 1494.

DOCUMENT: 

The modern field was established by the Italian mathematician Luca Pacioli in 1494.

CLAIMS: 

1. The wizard is an engineer.
2. The wizard knows some about accounting.
3. Modern accounting was established in 1494.

CLAIM ANNOTATION:

Now, you will go through each claim one by one:

The wizard is an engineer.

How should this claim be handled? 

- This claim is correct. Edit this claim Delete this claim

How does the claim relate to the document? 

- Verifiable Contradicted Lacking evidence Out of scope Abstention

The wizard knows some about accounting.

How should this claim be handled? 

- This claim is correct. Edit this claim Delete this claim

How does the claim relate to the document? 

- Verifiable Contradicted Lacking evidence Out of scope Abstention

Modern accounting was established in 1494.

How should this claim be handled? 

- This claim is correct. Edit this claim Delete this claim

How does the claim relate to the document? 

- Verifiable Contradicted Lacking evidence Out of scope Abstention

Add new claim(s): 

+ Add a new claim

Justification or notes (optional):

C Significance Testing of Model Performance

Model	Comparison	Δ	p-value	Sig.	Discordant (b, c)
GPT-5	VISTA – LLM-as-Judge	2.8	0.201473	ns	b=61, c=77
	VISTA – FActScore	1.0	0.051989	ns	b=64, c=89
	LLM-as-Judge – FActScore	-1.8	0.497564	ns	b=65, c=74
GPT-4o	VISTA – LLM-as-Judge	6.2	0.013712	*	b=90, c=59
	VISTA – FActScore	6.2	0.020741	*	b=100, c=69
	LLM-as-Judge – FActScore	0.0	1.000000	ns	b=88, c=88
DeepSeek	VISTA – LLM-as-Judge	6.4	0.022768	*	b=109, c=77
	VISTA – FActScore	0.8	0.812616	ns	b=82, c=78
	LLM-as-Judge – FActScore	-5.6	0.033572	*	b=67, c=95
Llama-70B	VISTA – LLM-as-Judge	6.6	0.005683	**	b=84, c=51
	VISTA – FActScore	6.4	0.022035	*	b=108, c=76
	LLM-as-Judge – FActScore	-0.2	1.000000	ns	b=97, c=98
Llama-8B	VISTA – LLM-as-Judge	10.4	0.001445	**	b=155, c=103
	VISTA – FActScore	10.6	0.000499	***	b=139, c=86
	LLM-as-Judge – FActScore	0.2	1.000000	ns	b=106, c=105
Qwen-32B	VISTA – LLM-as-Judge	18.0	0.000000	***	b=176, c=86
	VISTA – FActScore	11.2	0.000013	***	b=109, c=53
	LLM-as-Judge – FActScore	-6.8	0.013158	*	b=72, c=106
Qwen-8B	VISTA – LLM-as-Judge	10.4	0.000311	***	b=127, c=75
	VISTA – FActScore	7.4	0.006338	**	b=106, c=69
	LLM-as-Judge – FActScore	-3.2	0.260732	ns	b=70, c=85
Mistral-7B	VISTA – LLM-as-Judge	9.8	0.007287	**	b=185, c=136
	VISTA – FActScore	6.0	0.100477	ns	b=171, c=141
	LLM-as-Judge – FActScore	-3.8	0.153215	ns	b=70, c=69

Table 7: **AIS:** Pairwise performance differences between VISTA, LLM-as-Judge, and FActScore. Δ is the absolute accuracy difference (System1 – System2). Statistical significance from McNemar’s test: * $p < .05$, ** $p < .01$, *** $p < .001$, ns $> .05$. The final column (“Discordant (b, c)”) reports the number of items where System1 was correct and System2 incorrect (b), and vice versa (c).

Model	Comparison	Δ	p-value	Sig.	Discordant (b, c)
GPT-5	VISTA – LLM-as-Judge	17.2	0.000000	***	b=109, c=34
	VISTA – FActScore	16.2	0.000000	***	b=116, c=46
	LLM-as-Judge – FActScore	-1.0	0.726876	ns	b=63, c=68
GPT-4o	VISTA – LLM-as-Judge	12.8	0.000000	***	b=100, c=36
	VISTA – FActScore	17.4	0.000000	***	b=120, c=33
	LLM-as-Judge – FActScore	4.6	0.082626	ns	b=92, c=69
DeepSeek	VISTA – LLM-as-Judge	13.8	0.000000	***	b=93, c=24
	VISTA – FActScore	24.8	0.000000	***	b=120, c=31
	LLM-as-Judge – FActScore	11.0	0.067001	ns	b=64, c=44
Llama-70B	VISTA – LLM-as-Judge	-1.6	0.519491	ns	b=55, c=63
	VISTA – FActScore	24.4	0.000000	***	b=137, c=49
	LLM-as-Judge – FActScore	26.0	0.000000	***	b=138, c=42
Llama-8B	VISTA – LLM-as-Judge	12.8	0.000001	***	b=143, c=79
	VISTA – FActScore	20.0	0.000000	***	b=168, c=64
	LLM-as-Judge – FActScore	7.2	0.005029	**	b=118, c=78
Qwen-32B	VISTA – LLM-as-Judge	33.8	0.000000	***	b=183, c=15
	VISTA – FActScore	16.2	0.000000	***	b=104, c=24
	LLM-as-Judge – FActScore	-17.6	0.000000	***	b=18, c=106
Qwen-8B	VISTA – LLM-as-Judge	10.4	0.000045	***	b=107, c=55
	VISTA – FActScore	16.2	0.000000	***	b=132, c=51
	LLM-as-Judge – FActScore	5.8	0.009966	**	b=74, c=46
Mistral-7B	VISTA – LLM-as-Judge	14.6	0.000017	***	b=178, c=105
	VISTA – FActScore	18.2	0.000000	***	b=199, c=108
	LLM-as-Judge – FActScore	3.6	0.156343	ns	b=81, c=63

Table 8: **BEGIN**: Pairwise performance differences between VISTA, LLM-as-Judge, and FActScore. Δ denotes the absolute accuracy difference ($\text{System}_1 - \text{System}_2$). Statistical significance via McNemar’s test: * $p < .05$, ** $p < .01$, *** $p < .001$, ns $> .05$. The final column (“Discordant (b, c)”) reports counts where System_1 was correct and System_2 was incorrect (b), and vice versa (c).

Model	Comparison	Δ	p-value	Sig.	Discordant (b, c)
GPT-5	VISTA – LLM-as-Judge	3.91	0.041372	*	b=95, c=68
	VISTA – FActScore	3.51	0.01185	*	b=72, c=44
	LLM-as-Judge – FActScore	-0.4	1.000000	ns	b=85, c=84
GPT-4o	VISTA – LLM-as-Judge	2.34	0.202924	ns	b=68, c=53
	VISTA – FActScore	8.29	0.000019	***	b=102, c=49
	LLM-as-Judge – FActScore	5.95	0.006512	**	b=112, c=74
DeepSeek	VISTA – LLM-as-Judge	3.13	0.077262	ns	b=68, c=48
	VISTA – FActScore	7.51	0.000014	***	b=84, c=36
	LLM-as-Judge – FActScore	4.38	0.029246	*	b=91, c=63
Llama-70B	VISTA – LLM-as-Judge	2.82	0.101433	ns	b=63, c=45
	VISTA – FActScore	8.45	0.000076	***	b=118, c=64
	LLM-as-Judge – FActScore	5.63	0.006423	**	b=101, c=65
Llama-8B	VISTA – LLM-as-Judge	17.21	0.000000	***	b=217, c=107
	VISTA – FActScore	7.51	0.001261	**	b=131, c=83
	LLM-as-Judge – FActScore	-9.7	0.000705	***	b=132, c=194
Qwen-32B	VISTA – LLM-as-Judge	17.06	0.000000	***	b=220, c=111
	VISTA – FActScore	7.51	0.000019	***	b=86, c=38
	LLM-as-Judge – FActScore	-9.55	0.000785	***	b=130, c=191
Qwen-8B	VISTA – LLM-as-Judge	7.36	0.001826	**	b=113, c=70
	VISTA – FActScore	8.61	0.000002	***	b=92, c=41
	LLM-as-Judge – FActScore	1.25	0.613457	ns	b=100, c=92
Mistral-7B	VISTA – LLM-as-Judge	24.41	0.000000	***	b=276, c=120
	VISTA – FActScore	20.19	0.000000	***	b=231, c=102
	LLM-as-Judge – FActScore	-4.22	0.123384	ns	b=129, c=156

Table 9: **FADE**: Pairwise performance differences between VISTA, LLM-as-Judge, and FActScore. Δ denotes the absolute accuracy difference ($\text{System}_1 - \text{System}_2$). Statistical significance via McNemar’s test: * $p < .05$, ** $p < .01$, *** $p < .001$, ns $> .05$. The final column (“Discordant (b, c)”) reports counts where System_1 was correct and System_2 was incorrect (b), and vice versa (c).

Model	Comparison	Δ	p-value	Sig.	Discordant (b, c)
GPT-5	VISTA – LLM-as-Judge	14.89	0.000003	***	b=549, c=404
	VISTA – FActScore	12.51	0.001802	**	b=462, c=371
	LLM-as-Judge – FActScore	-2.38	0.052566	ns	b=347, c=401
GPT-4o	VISTA – LLM-as-Judge	19.52	0.000000	***	b=609, c=174
	VISTA – FActScore	17.14	0.000000	***	b=538, c=156
	LLM-as-Judge – FActScore	-2.38	0.05305	ns	b=335, c=388
DeepSeek	VISTA – LLM-as-Judge	26.25	0.000000	***	b=757, c=172
	VISTA – FActScore	17.95	0.000000	***	b=586, c=168
	LLM-as-Judge – FActScore	-8.3	0.000000	***	b=264, c=449
Llama-70B	VISTA – LLM-as-Judge	-0.54	0.664223	ns	b=315, c=327
	VISTA – FActScore	17.76	0.000000	***	b=598, c=202
	LLM-as-Judge – FActScore	18.3	0.000000	***	b=621, c=213
Llama-8B	VISTA – LLM-as-Judge	16.96	0.000000	***	b=630, c=252
	VISTA – FActScore	10.59	0.000000	***	b=617, c=381
	LLM-as-Judge – FActScore	-6.37	0.000000	***	b=621, c=213
Qwen-32B	VISTA – LLM-as-Judge	39.84	0.000000	***	b=1016, c=125
	VISTA – FActScore	17.32	0.000000	***	b=554, c=68
	LLM-as-Judge – FActScore	-22.52	0.000000	***	b=110, c=615
Qwen-8B	VISTA – LLM-as-Judge	18.63	0.000000	***	b=632, c=231
	VISTA – FActScore	16.91	0.000000	***	b=569, c=212
	LLM-as-Judge – FActScore	-1.72	0.393936	ns	b=351, c=375
Mistral-7B	VISTA – LLM-as-Judge	25.58	0.000000	***	b=973, c=403
	VISTA – FActScore	23.6	0.000000	***	b=967, c=441
	LLM-as-Judge – FActScore	-1.98	0.112904	ns	b=346, c=390

Table 10: **FaithDial:** Pairwise performance differences between VISTA, LLM-as-Judge, and FActScore. Δ denotes the absolute accuracy difference ($\text{System}_1 - \text{System}_2$). Statistical significance via McNemar’s test: * $p < .05$, ** $p < .01$, *** $p < .001$, ns $> .05$. The final column (“Discordant (b, c)”) reports counts where System_1 was correct and System_2 was incorrect (b), and vice versa (c).

D Confusion Matrices for Category Assignment by Models

This appendix provides the claim-level confusion matrices corresponding to the results summarized in Table 5. Each matrix compares the model’s predicted factuality category for each atomic claim against the consensus human annotation. Rows represent the true (human) categories, and columns represent the model predictions. Diagonal entries correspond to correctly classified claims, while off-diagonal counts indicate category confusions. Counts include all 888 consensus-annotated claims across evaluation turns.

Table 11: Claim-level confusion matrix for **GPT-5**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	18	0	1	0	2	1	22
CONTRADICTED	0	6	2	0	0	0	8
LACKING EVIDENCE	1	11	140	0	20	41	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	9	3	22	1	175	17	227
VERIFIED	1	8	23	0	1	385	418
Total	29	28	188	1	198	444	888

Table 12: Claim-level confusion matrix for **GPT-4o**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	20	0	1	0	1	0	22
CONTRADICTED	0	6	1	0	0	1	8
LACKING EVIDENCE	0	23	109	0	22	59	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	15	6	29	0	162	15	227
VERIFIED	0	21	21	0	1	375	418
Total	35	56	161	0	186	450	888

Table 13: Claim-level confusion matrix for **DeepSeek**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	19	0	1	0	2	0	22
CONTRADICTED	0	3	3	0	0	2	8
LACKING EVIDENCE	0	2	145	0	14	52	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	17	0	41	0	149	20	227
VERIFIED	0	3	22	0	1	392	418
Total	36	8	212	0	166	466	888

Table 14: Claim-level confusion matrix for **Llama-70B**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	2	0	0	0	2	18	22
CONTRADICTED	0	5	0	0	0	3	8
LACKING EVIDENCE	0	26	57	0	28	102	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	0	1	4	0	154	68	227
VERIFIED	0	16	0	0	0	402	418
Total	2	48	61	0	184	593	888

Table 15: Claim-level confusion matrix for **Llama-8B**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	6	0	6	0	6	4	22
CONTRADICTED	0	5	0	0	0	3	8
LACKING EVIDENCE	0	13	62	0	29	109	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	3	1	12	0	161	50	227
VERIFIED	0	16	9	0	2	391	418
Total	9	35	89	0	198	557	888

Table 16: Claim-level confusion matrix for **Qwen3-32B**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	20	0	0	0	1	1	22
CONTRADICTED	0	3	0	0	0	5	8
LACKING EVIDENCE	0	23	30	0	58	102	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	13	3	8	0	148	55	227
VERIFIED	0	6	0	0	3	409	418
Total	33	35	38	0	210	572	888

Table 17: Claim-level confusion matrix for **Qwen3-8B**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	13	0	2	0	7	0	22
CONTRADICTED	0	2	4	0	0	2	8
LACKING EVIDENCE	5	5	77	0	47	79	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	9	0	24	0	160	34	227
VERIFIED	0	4	19	0	5	390	418
Total	27	11	126	0	219	505	888

Table 18: Claim-level confusion matrix for **Mistral-7B**.

Human \ Model	ABSTENTION	CONTRADICTED	LACKING EVIDENCE	NONE	OUT-OF-SCOPE	VERIFIED	Total
ABSTENTION	13	0	1	0	8	0	22
CONTRADICTED	0	0	1	0	3	4	8
LACKING EVIDENCE	0	0	13	3	105	92	213
NONE	0	0	0	0	0	0	0
OUT-OF-SCOPE	6	0	4	3	175	39	227
VERIFIED	0	0	7	4	27	380	418
Total	19	0	26	10	318	515	888

E Example Annotation Discrepancies

Below is an illustrative example (category 6) from the FaithDial dataset where conversational context affects factuality labeling. The original dataset marked the target turn as UNVERIFIABLE, but VISTA and our human annotators judged it as VERIFIED once the dialogue history was considered.

CONVERSATION CONTEXT:

wizard: I love the Chainsmokers! The Chainsmokers is an American DJ/production duo.
apprentice: I have never heard of them? Tell me more—it sounds like something I would like.

TARGET TURN:

wizard: Well, the EDM-pop duo achieved a breakthrough with their 2014 song #Selfie.

DOCUMENT:

The Chainsmokers: The EDM-pop duo achieved a breakthrough with their 2014 song #Selfie, which was a top-twenty single in several countries.

CLAIMS:

1. The Chainsmokers achieved a breakthrough with their 2014 song #Selfie. – VERIFIED
2. The Chainsmokers achieved a breakthrough. – VERIFIED
3. The Chainsmokers is an EDM-pop duo. – VERIFIED

The original annotation likely marked this turn as unverifiable because the referent of “the EDM-pop duo” is ambiguous without the prior context. Once the preceding turns are included, however, the claim is easily resolved and verifiable. This example illustrates how conversational grounding can shift factuality judgments and highlights the limitations of single-turn annotation protocols.