
GEM-BENCH: A BENCHMARK FOR AD-INJECTED RESPONSE GENERATION WITHIN GENERATIVE ENGINE MARKETING

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ABSTRACT

Generative Engine Marketing (GEM) is an emerging ecosystem for monetizing generative engines, such as LLM-based chatbots, by seamlessly integrating relevant advertisements into their responses. At the core of GEM lies the generation and evaluation of ad-injected responses. However, existing benchmarks are not specifically designed for this purpose, which limits future research. To address this gap, we propose GEM-BENCH, the first comprehensive benchmark for ad-injected response generation in GEM. GEM-BENCH includes three curated datasets covering both chatbot and search scenarios, a metric ontology that captures multiple dimensions of user satisfaction and engagement, and several baseline solutions implemented within an extensible multi-agent framework. Our preliminary results indicate that, while simple prompt-based methods achieve reasonable engagement such as click-through rate, they often reduce user satisfaction. In contrast, approaches that insert ads based on pre-generated ad-free responses help mitigate this issue but introduce additional overhead. These findings highlight the need for future research on designing more effective and efficient solutions for generating ad-injected responses in GEM. The benchmark and all related resources are publicly available at <https://gem-bench.org/>.

1 INTRODUCTION

Large Language Models (LLMs) and general-purpose AI assistants, such as ChatGPT and Gemini, are fundamentally reshaping how users interact with information by providing direct, conversational, and context-aware answers. This shift is disrupting traditional search engine marketing (SEM) that relies on clicking the sponsored page on the search engine. Notably, Brodsky (2023) reports that 35% of casual users find LLMs more helpful for obtaining information than search engines. A recent study Chapekis & Lieb (2025) confirms that Google users' click-through rate (CTR) is 8% when AI summaries are present, compared to 15% without them, representing nearly a 47% decline in CTR on traditional links when AI summaries appear. Meanwhile, to monetize LLM models, service providers such as Bing Chat Sainsbury-Carter (2023) and Perplexity Team (2024) have begun experimenting with integrating advertisements directly within LLM-generated responses, referred to as *generative engine marketing* (GEM).

This work focuses on a linchpin problem of GEM, called the ad-injected response (**AIR**) generation. Given an advertisement database \mathcal{D} and an LLM \mathcal{M} , the **AIR** generation problem takes as input a user query and possible context (e.g., user profile or chat history) and aims to seamlessly integrate relevant ad descriptions from \mathcal{D} into the \mathcal{M} -generated response to this query. As a new research direction, datasets, evaluation metrics, and solutions for **AIR** generation remain limited. Existing LLM

benchmark datasets Hendrycks et al. (2020; 2021); Zheng et al. (2023b;a) contain many questions from domains that are fundamentally unsuitable for ad integration, such as mathematics, coding, and data labeling. Moreover, common text quality metrics such as ROUGE Lin (2004) and BLEU Papineni et al. (2002) evaluate responses against reference texts, which introduces bias when ads are injected into pre-generated templates or responses. At the same time, recent LLM-as-a-Judge approaches Zheng et al. (2023b;a) are not tailored for evaluating AIR, since they fail to capture nuanced aspects of user experience such as trust or jump-out feeling Tang et al. (2024). Regarding existing solutions, Feizi et al. (2023) propose the first conceptual framework for LLM advertising. In this framework, the main idea for AIR generation is to first produce an ad-free response and then modify it by inserting suitable ads from \mathcal{D} . However, no implementation or empirical evaluation is provided. Tang et al. (2024) design a chatbot for AIR generation in which relevant ads are inserted into the system prompt to personalize responses and promote products or brands, yet its performance has not been extensively studied.

To address these issues, we introduce GEM-BENCH, the first comprehensive benchmark for AIR generation in GEM. GEM-BENCH consists of curated datasets, a measurement ontology, and several vanilla solutions for evaluating AIR generation in GEM. Specifically, we curate two datasets, MT-Human and LM-Market, for chatbot scenarios, containing user queries to ChatGPT that are suitable for ad injection, and one dataset, CA-Prod, that simulates the AI overview feature in search engines. To evaluate the quality of AIR, we propose a metric ontology that captures multiple aspects of user satisfaction and engagement. This ontology can also be applied to other stages of GEM, such as estimating response quality during bidding and auction. Finally, we implement several baseline solutions inspired by the conceptual framework Feizi et al. (2023) within a multi-agent paradigm. It decouples agents, tools, and workflows, enabling flexible development of future solutions.

Our preliminary experiments reveal clear trade-offs among different solutions. We find that the simple system prompt-based approach Tang et al. (2024), while achieving relatively high engagement (e.g., 6.5% higher CTR), often compromises user satisfaction by reducing response accuracy and trust. In contrast, baselines inspired by Feizi et al. (2023), which first generate ad-free responses and subsequently inject advertisements with refinement, substantially improve user satisfaction and engagement. These methods achieve relative gains of up to 39.8% in accuracy, 89.3% in personality, and 62.9% in trust across multiple datasets. These improvements are consistently validated by diverse LLM judges, reaching a strong consensus. However, this baseline incurs additional overhead, consuming about 2 \times more output tokens than the system prompt-based solution.

To summarize, we make the following contributions in this work:

- We introduce GEM-BENCH, the first comprehensive benchmark for evaluating ad-injected response (AIR) generation in generative engine marketing (GEM).
- We curate and preprocess three datasets from two real-world scenarios, chatbots and search engines, where AIR generation can be effectively applied.
- We design an evaluation ontology for assessing the quality of AIR, considering multiple aspects of user satisfaction and engagement.
- We propose several AIR generation baselines implemented in an extensible multi-agent manner, enabling researchers to easily experiment with and develop new solutions in the future.

2 PRELIMINARIES

This section first introduces the existing frameworks for search engine marketing (SEM) and generative engine marketing (GEM), followed by formulating the Ad-Injected Response (AIR) Generation problem and briefly reviewing the existing solution, named Ad-Chat Tang et al. (2024). Additional related work is summarized in Appendix A.

2.1 SEM AND GEM

The online advertising ecosystem consists of three stakeholders: platforms, users, and advertisers. *Platforms* connect advertisers with users by delivering targeted ads, aiming to balance user experience with sustainable monetization. *Users* consume content and may interact with ads, expecting minimal disruption. *Advertisers* pay for placements to reach target audiences and drive conversions.

Search Engine Marketing (SEM). As a primary channel of online advertising, SEM displays sponsored results in response to user queries on a search engine. The standard paradigm Lahaie et al. (2007) typically consists of the following core stages:

- *Stage 1: Offline bidding.* Advertisers first configure their campaigns by placing monetary bids on one or more keywords relevant to their ads.
- *Stage 2: Query processing.* When a user submits a query, the platform retrieves a ranked list of organic results and, in parallel, collects a set of candidate ads that match the query.
- *Stage 3: Slot identification.* Based on the query and result list, the platform determines how many ad slots will be displayed.
- *Stage 4: Performance prediction.* For each advertiser–slot pair in the candidate set, the platform predicts the likelihood of a user clicking the ad, i.e., the click-through rate (CTR).
- *Stage 5: Auction and allocation.* Finally, the platform runs an auction to allocate ads across the available slots, aiming to maximize overall expected value by considering bid amounts and CTR.

Generative Engine Marketing (GEM). Analogous to SEM, Feizi et al. (2023) propose a conceptual framework for generative engine marketing (GEM), in which an LLM integrates native advertisements directly into its generated responses. This framework mirrors the five stages of SEM but extends them to the context of LLMs. In particular, during query processing (stage 2), the system first generates an ad-free response to the user query and then performs an additional modification step to inject a relevant ad candidate into the output.

Although the overall pipeline can be adapted from SEM, each stage of GEM introduces unique challenges and open questions. In the bidding stage, a central issue is determining what exactly advertisers would bid for. In the slot identification stage, the absence of explicit ad slots raises two key problems: deciding whether a query is suitable for ad inclusion and, if so, identifying insertion points within unstructured text that may contain multiple candidates. For performance prediction and auction, a fundamental challenge is estimating click-through rates (CTR) from unstructured responses. Beyond explicit engagement signals, the system must also evaluate and predict user satisfaction with the generated content. Finally, in the ad-injected response (AIR) generation stage, the central problem is how to produce output that *(i) incorporates ads seamlessly without degrading the user experience, and (ii) satisfies the advertiser’s objectives*.

2.2 AD-INJECTED RESPONSE GENERATION

In this work, we focus on the Ad-Injected Response (AIR) Generation problem. It is the linchpin step of GEM, since regardless of how the overall framework evolves, the AIR is eventually what the system delivers to the user.

Formulation. We represent the results of the offline bidding stage as an advertisement database (AdDB) \mathcal{D} , where each row $d_i \in \mathcal{D}$ contains the bidding string, its associated embedding, bidding price, and product meta-information (such as advertiser, description, URL, and ad creatives). Given an AdDB \mathcal{D} , an LLM \mathcal{M} , and an integer k , the AIR generation problem takes as input a user query and possible context (e.g., user profile or chat history) and aims to return an ad-injected response (AIR) that seamlessly integrates k unstructured and relevant ads from \mathcal{D} into the \mathcal{M} -generated response to the query. The objective is to maximize both user satisfaction and user engagement. Satisfaction reflects the user experience when interacting with the model \mathcal{M} and can be measured by factors such as response latency and content quality. Engagement, on the other hand, captures whether the user notices the ad, has a positive attitude toward it, and potentially clicks the in-text ad link, which are the dimensions of primary interest to advertisers. For simplicity, we assume that every query discussed here has already passed the slot identification stage and is therefore suitable for ad insertion, and we set $k = 1$ in the subsequent discussion.

Existing Solution: Ad-Chat. Beyond the idea of inserting a relevant ad into an original response Feizi et al. (2023), Tang et al. (2024) propose Ad-Chat, which integrates native ads into the system prompt when responding to user queries. As illustrated in Figure 1, given a user query and possible user profile and chat history, Ad-Chat first uses the LLM \mathcal{M} to assign a topic from Google Topics Google Privacy Sandbox Team (2024) to the conversation. It then instructs \mathcal{M} to select the most suitable product from the bidding products associated with that topic. Finally, Ad-Chat in-

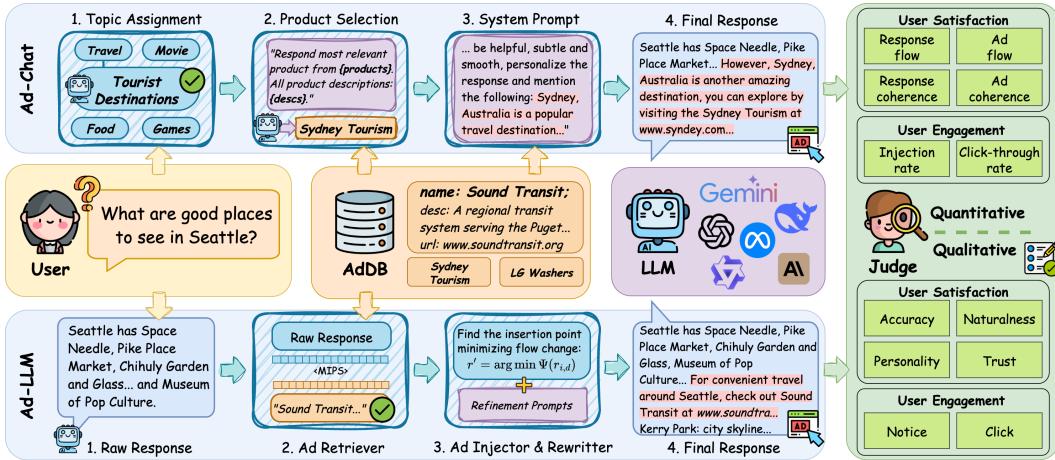


Figure 1: The illustration of two existing workflows for ad-injected response (AIR) generation in GEM and the proposed measurement ontologies.

Table 1: Statistics of curated datasets.

Dataset	Scenario	AdDB			Queries		
		#Ads	#Topics	Source	#Queries	#Topics	Source
MT-Human	Chatbot	6,556	576	Tang et al. (2024)	10	1	Zheng et al. (2023b)
LM-Market	Chatbot	6,556	576	Tang et al. (2024)	100	3	Zheng et al. (2023a)
CA-Prod	Search Engine	2,215	6	Zhu et al. (2022)	120	6	Zhu et al. (2022)

serts the ad with its description and URL into the system prompt, aiming to appeal to the user and personalize the response while promoting products, ultimately generating the AIR.

3 GEM-BENCH

This section introduces the main components of GEM-BENCH: curated datasets for both chatbot and search engine scenarios, a measurement ontology for evaluating AIR, and a modular framework implementation. Detailed descriptions of each component are provided in Appendices B, C, and D.

3.1 DATASETS

Chatbot: MT-Human and LM-Market. For the chatbot scenario, we construct two query sets. MT-Human is curated from MT-Bench Zheng et al. (2023b), where each query is manually examined for suitability for ad insertion. We retain all 10 first-turn queries from the humanities category to form the MT-Human dataset, including examples such as “What are some business etiquette norms when doing business in Japan.” Due to the large scale of LMSYS-Chat-1M Zheng et al. (2023a), LM-Market is derived through a multi-stage pipeline: we filter for single-turn English queries, cluster them into topics, and then apply LLM-assisted scoring followed by manual verification to retain queries with high ad-injection potential. In total, 100 queries are selected across three domains: *travel planning*, *recipe recommendation*, and *software tools comparison*. The associated AdDB \mathcal{D} is adopted from Ad-Chat Tang et al. (2024), which contains 6,556 manually verified products, brands, and organizations spanning 25 main topics and 576 subtopics.

Search Engine: CA-Prod. For the search engine scenario, we construct CA-Prod from a commercial dataset of query-ad pairs with human-annotated relevance labels Zhu et al. (2022). Following a procedure similar to LM-Market, we cluster ads into six representative domains, such as *nutrition supplements*, *women’s dresses*, and *Android devices*, and assign topics to queries according to their relevant ads. After filtering out extremely sparse or dense cases, we retain 120 queries associated with 2,215 unique products. To mimic the AI overview feature in modern search engines, the infer-

Table 2: Qualitative evaluation ontology for AIR generation.

Aspects	Metrics	Considered Dimensions
User Satisfaction	Accuracy	Relevance, Accuracy
	Naturalness	Interruptiveness, Authenticity
	Personality	Helpfulness, Salesmanship
	Trust	Credibility, Bias
User Engagement	Notice Click	Notice, Attitude Notice, Click

ence model \mathcal{M} is set to generate a concise overview for each keyword query, helping users quickly grasp the topic. The statistics of the curated datasets are summarized in Table 1.

3.2 MEASUREMENT ONTOLOGY

Quantitative Metrics. Consider a response r with $\ell = |r| > 1$ sentences, where s_i denotes the i -th sentence and \mathbf{s}_i its embedding. Let $\text{sim}(\cdot, \cdot)$ denote cosine similarity, and $\bar{\mathbf{s}}$ the mean embedding of all sentences. To capture user satisfaction, we define two global metrics *response flow* and *response coherence*, and two corresponding local metrics *ad flow* and *ad coherence*. Specifically, *response flow* measures semantic continuity across adjacent sentences:

$$f(r) = \frac{1}{\ell-1} \sum_{i=1}^{\ell-1} \text{sim}(\mathbf{s}_i, \mathbf{s}_{i+1}),$$

while *response coherence* evaluates how consistently each sentence aligns with the overall theme:

$$c(r) = \frac{1}{\ell} \sum_{i=1}^{\ell} \text{sim}(\mathbf{s}_i, \bar{\mathbf{s}}).$$

Ad flow measures whether semantic transitions around an injected ad remain smooth, and *ad coherence* captures how well the ad aligns with the non-ad content. For engagement, we adopt *injection rate* to record whether a response contains an ad, and *click-through rate* to estimate further user conversion.

Qualitative Metrics. Beyond similarity-based measures, we include six LLM-as-a-Judge metrics that capture user satisfaction by *accuracy*, *naturalness*, *personality*, and *trust*, and user engagement by *notice* and *click*. Each metric is evaluated along two dimensions, summarized in Table 2, and the resulting ratings are mapped to discrete levels $\{0, 30, 60, 90\}$ to ensure transparent and consistent judgment. Importantly, these metrics and dimensions are grounded in a qualitative codebook derived from real user studies Tang et al. (2024), thereby ensuring validity and practical relevance.

3.3 AD-LLM IMPLEMENTATION

To implement the conceptual framework proposed by Feizi et al. (2023), we adopt a multi-agent paradigm and provide a modular implementation for AIR generation, called Ad-LLM. As illustrated in Figure 1, Ad-LLM can be regarded as an application of retrieval-augmented generation (RAG) and follows a chain-like multi-agent workflow consisting of four agents: an ad-free response generator, an ad retriever, an ad injector, and a final response rewriter.

At the core of this workflow is the injection step, which determines both which ad to insert and where to place it. We formulate this as minimizing the *flow disturbance* at the injection point. For a response r with ℓ sentences, let $r_{i,d}$ denote the new response obtained by inserting an ad sentence s_d after s_i . Given a candidate set \mathcal{D}_t of retrieved ads, the injection objective is defined as

$$r' = \arg \min_{i \in [\ell-1], d \in \mathcal{D}_t} \Psi(r_{i,d}),$$

where $\Psi(r_{i,d})$ measures the semantic flow disruption introduced by the insertion. A simple formulation is

$$\Psi(r_{i,d}) = \text{sim}(\mathbf{s}_i, \mathbf{s}_{i+1}) - \frac{\text{sim}(\mathbf{s}_i, \mathbf{s}_d) + \text{sim}(\mathbf{s}_d, \mathbf{s}_{i+1})}{2}.$$

This objective captures the intuition that the optimal ad and insertion point are those that minimally disrupt the semantic flow, allowing ads to blend smoothly into the surrounding context. This modular workflow provides a reproducible and extensible baseline for future research.

Table 3: Quantitative effectiveness evaluation. RF: Response Flow, RC: Response Coherence, AF: Ad Flow, AC: Ad Coherence, IR: Injection Rate, CTR: Click-Through Rate.

Dataset	Solution	Quantitative Metrics						
		RF	RC	AF	AC	IR	CTR	
MT-Human	Ad-Chat	82.06	41.12	43.48	62.39	66.00	—	59.01
	GI-R	87.06	41.70	43.10	66.32	100.00	—	67.64
	GIR-R	77.08	39.95	41.77	61.67	100.00	—	64.09
	GIR-P	77.60	40.40	41.56	61.72	100.00	—	64.25
LM-Market	Ad-Chat	82.26	54.30	42.96	66.18	95.82	—	68.30
	GI-R	84.09	50.38	44.37	68.81	100.00	—	69.53
	GIR-R	73.35	51.23	42.53	65.60	100.00	—	66.54
	GIR-P	74.38	49.95	42.15	65.43	100.00	—	66.38
CA-Prod	Ad-Chat	85.92	43.52	35.99	65.34	100.00	42.02	62.13
	GI-R	86.12	63.49	42.10	69.46	100.00	35.23	66.07
	GIR-R	81.07	62.58	43.09	66.83	100.00	35.23	64.80
	GIR-P	77.87	61.99	42.92	67.12	100.00	39.45	64.89

Table 4: Effectiveness evaluation in terms of qualitative ontology.

Dataset	Solution	Qualitative Metrics						
		Accuracy	Naturalness	Personality	Trust	Notice	Click	
MT-Human	Ad-Chat	72.60	51.00	68.40	61.80	72.60	64.20	65.10
	GI-R	83.40	39.60	79.80	68.40	74.40	72.60	69.70
	GIR-R	85.80	52.80	74.40	73.20	82.80	79.20	74.70
	GIR-P	82.80	53.40	74.40	70.20	81.60	81.00	73.90
LM-Market	Ad-Chat	61.97	52.54	57.38	55.47	77.46	78.01	63.81
	GI-R	79.55	47.46	76.49	69.30	75.11	74.84	70.46
	GIR-R	80.32	62.49	71.88	70.47	80.14	77.10	73.73
	GIR-P	78.96	60.72	71.63	69.48	79.66	75.52	72.66
CA-Prod	Ad-Chat	42.60	36.38	25.03	22.66	88.12	88.25	50.51
	GI-R	53.76	26.55	44.85	36.69	80.09	85.08	54.50
	GIR-R	59.56	34.45	46.97	36.92	84.97	87.16	58.34
	GIR-P	59.19	35.40	47.39	36.88	84.34	87.24	58.41

4 EXPERIMENTS

GEM-BENCH aims to answer the following three research questions:

- **RQ1:** How effective are solutions in terms of quantitative and qualitative evaluation ontologies?
- **RQ2:** How do the core agents and their implementations impact the effectiveness of Ad-LLM?
- **RQ3:** How much does each solution cost in terms of waiting time and monetary cost?

GEM-BENCH evaluates the performance of four solutions: the existing solution Ad-Chat Tang et al. (2024) and three instances, GI-R, GIR-R, and GIR-P, of the implemented framework Ad-LLM across the aforementioned datasets and evaluation metrics. For the three Ad-LLM instances, GIR represents completing all three agents to Generate, Inject, and Rewrite, but GI skips the final rewriting step. The suffixes -P and -R indicate whether the ads are retrieved based on the user prompt or the original response, respectively. Unless otherwise specified, all solutions use doubaot-1-5-lite-32k as the base LLM, and their results are evaluated using gpt-4.1-mini. Additionally, for quantitative evaluation and Ad-LLM instances, we set the embedding model to text-embedding-3-small by default. For Ad-Chat, we follow its original implementation and retain the default configuration.

4.1 EFFECTIVENESS EVALUATION (RQ1)

Ad-LLM outperforms Ad-Chat in user satisfaction and user engagement. Table 3 and Table 4 report the performance of Ad-Chat and three Ad-LLM instances in terms of both quantitative and qualitative evaluation ontologies across three datasets. Overall, the best Ad-LLM instance improves Ad-Chat by 14.6%, 1.8%, and 6.3% in terms of overall quantitative metrics, and by 14.8%, 15.6%, and 15.64% in terms of overall qualitative metrics on MT-Human, LM-Market, and CA-Prod, re-

Table 5: Qualitative overall scores comparison across different LLM judges.

Dataset	Solution	Judge Model			
		gpt-4.1-mini	qwen-max	claude-3-5-haiku	kimi-k2
MT-Human	Ad-Chat	65.10	56.90	52.50	46.90
	GI-R	69.70	57.70	65.30	52.80
	GIR-R	74.70	61.70	67.40	61.00
	GIR-P	73.90	60.90	64.10	57.10
LM-Market	Ad-Chat	63.81	55.99	47.66	42.47
	GI-R	70.46	57.07	63.21	49.91
	GIR-R	73.73	61.35	66.00	55.00
	GIR-P	72.66	59.46	64.48	53.28
CA-Prod	Ad-Chat	50.51	46.99	28.32	22.51
	GI-R	54.50	44.77	43.78	23.12
	GIR-R	58.34	50.57	45.03	30.75
	GIR-P	58.41	50.73	45.34	31.20

spectively. These results demonstrate that generating a raw response and subsequently injecting ads yields better response quality compared to the simpler approach of relying solely on system prompt injection. For specific user satisfaction and engagement dimensions, Ad-Chat consistently shows a substantial performance gap compared to Ad-LLM solutions across all three datasets, particularly in dimensions such as accuracy, personality, and trust. Notably, the best Ad-LLM instance improves Ad-Chat by up to 39.8%, 89.3%, and 62.9% across all datasets in terms of accuracy, personality, and trust, respectively. This can be explained by the fact that the system prompt of Ad-Chat is designed to appeal to users and personalize responses when promoting products. Consequently, this often causes the LLM to adopt a salesman-like role, which can compromise response accuracy and diminish user trust. Moreover, we observe that the injection rate (IR) of Ad-Chat is significantly lower than that of Ad-LLM solutions, even though only queries suitable for ad injection are considered. This is because the injection timing of Ad-Chat is determined by instructions in system prompts, which are difficult to measure and thus uncontrollable. Finally, we find that Ad-Chat achieves a higher click-through rate (CTR) in the search engine scenario, outperforming the best Ad-LLM instance by 6.5%. This suggests that retrieving relevant products using an LLM performs better than relying solely on the similarity of semantic embeddings.

Performance remains consistent across diverse LLM judges. Table 5 presents the overall qualitative scores of each solution as evaluated by four LLM judges: gpt-4.1-mini, qwen-max, claude-3-5-haiku, and kimi-k2. These judgment models are distinct from the base LLM doubaot-1-5-lite-32k, which helps mitigate the alignment issue wherein a judge model may favor outputs generated by models from the same family Fröbe et al. (2025). Notably, the Ad-LLM solutions consistently achieve the highest scores, with GIR-R ranking either first or second across all datasets according to all four LLM judges. This consistency indicates strong agreement among different LLMs regarding the effectiveness of Ad-LLM. The scores for individual qualitative dimensions closely mirror those reported in Table 4. Due to space constraints, we refer interested readers to Appendix E for detailed results from each LLM judge.

From the case study, Ad-LLM preserves answer quality with light and relevant ads, while Ad-Chat centers its responses on advertisements, often overshadowing the actual answer. As shown in Figure 2, Ad-Chat suggests using Megabus, a long-distance coach service that does not operate in Zürich. This response is not only unhelpful but factually incorrect. The Ad-LLM instance GIR-R, on the other hand, provides accurate and actionable directions: take tram line 13 or 14 from Zürich Main Station to the Sihlcity stop, a trip that takes about 10–15 minutes. The promotional element, a recommendation to use Citymapper, is light and relevant, since Citymapper is a tool for urban travel planning. Beyond this example, we observe consistent results in other scenarios, including queries about Seattle attractions, detox meal recommendations, and coworker gift suggestions. Detailed case studies are provided in Appendix F.

Question: How do you get from Zürich Main Station to the Sihlcity mall?	
Ad-Chat	GIR-R
<p>There are several ways to get from Zürich Main Station to the Sihlcity mall. You could take public transportation such as a tram or bus. However, if you're looking for a convenient and budget-friendly option, Megabus might be a great choice! Megabus is a budget intercity coach company that operates in Europe. It offers affordable travel between various destinations. To check schedules and book your journey from Zürich Main Station to the Sihlcity mall area, visit their website at https://us.megabus.com/. They can provide you with all the details you need for a smooth and cost-effective trip. This way, you can reach your destination without breaking the bank.</p>	<p>To travel from Zürich Main Station to the Sihlcity mall, you can take the tram. Here are the steps: Exit Zürich Main Station, find the nearby tram stop (tram lines 13 and 14 stop here), board the appropriate tram (either 13 or 14), and take it to the “Sihlcity” stop. Once there, you’ll be close to the mall. The journey typically takes around 10 - 15 minutes, depending on traffic. For easy urban transport and real-time departure and arrival times, as well as multimodal route planning, check out [Citymapper](https://citymapper.com/). Also, check the tram schedule at the station for the most accurate departures.</p>

Figure 2: A case study for a query about Zürich transport. The ad-related content is in blue.

Table 6: The effectiveness of GI-R based on different embedding models. Small: text-embedding-3-small, Mini: all-MiniLM-L6-v2.

Dataset	Model	Metrics						
		Accuracy	Naturalness	Personality	Trust	Notice	Click	Overall
MT-Human	Small	83.40	39.60	79.80	68.40	74.40	72.60	69.70
	Mini	88.00	37.00	78.00	70.00	73.00	67.00	68.83
LM-Market	Small	79.55	47.46	76.49	69.30	75.11	74.84	70.46
	Mini	76.77	45.47	77.87	68.57	70.93	71.65	68.54
CA-Prod	Small	53.76	26.55	44.85	36.69	80.09	85.08	54.50
	Mini	53.78	27.25	44.42	36.60	80.02	84.82	54.48

4.2 ABLATION STUDY (RQ2)

Based on the results in Table 3, Table 4, and Table 5, we derive the following insights regarding the three instances of Ad-LLM.

GI-R achieves better performance in terms of quantitative metrics but shows the lowest qualitative scores compared to the refinement instances GIR-R and GIR-P. Specifically, GI-R consistently outperforms refinement-based approaches in quantitative overall scores by relative improvements of up to 5.5%, 4.7%, and 2.0% on MT-Human, LM-Market, and CA-Prod. This is because GI-R explicitly determines the optimal injection position based on response flow, where flow is grounded in semantic similarity and thus directly benefits metrics such as RF, RC, and AC. Correspondingly, GI-R suffers relative degradations of up to -6.7%, -4.4%, and -2.0% in qualitative overall scores. The gap is especially pronounced in naturalness, where GI-R falls behind by as much as -25.8%. This degradation occurs because GI-R directly injects ad sentences without rewriting, making the insertion abrupt and less coherent with the context. By contrast, GIR-R and GIR-P incorporate rewriting to smooth the transition, thereby improving naturalness, trust, and personality, which explains their superior qualitative outcomes.

Ad retrieval based on response demonstrates stronger effectiveness in the chatbot scenario, while ad retrieval based on prompt performs better in the search engine scenario. For the MT-Human and LM-Market datasets, response-based retrieval GIR-R consistently outperforms prompt-based retrieval GIR-P. Notably, GIR-R achieves the best overall qualitative score, surpassing GIR-P by 1.3% as reported in Table 4. This superiority is consistently observed across different judge models. For example, under kimi-k2, GIR-R outperforms GIR-P with a relative gain of 3.9%. This advantage stems from the nature of chatbot interactions, where questions and responses often involve complex semantic relationships. For instance, when a user asks, “I often feel tired at work, what would you recommend”, the model’s response provides nuanced context that helps anchor ad injection in a meaningful way. In contrast, prompt-based retrieval GIR-P achieves superior qualitative performance on the CA-Prod dataset. As shown in Table 4, GIR-P achieves a

Table 7: Cost evaluation. ITTFT: extra input tokens to first token, OTTFT: extra output tokens to first token, Overall: aggregated cost.

Solution	MT-Human			LM-Market			CA-Prod		
	ITTFT	OTTFT	Overall	ITTFT	OTTFT	Overall	ITTFT	OTTFT	Overall
Ad-Chat	686.03	523.80	866.82	897.46	456.56	905.29	2911.49	217.68	1673.43
GI-R	125.83	503.73	566.65	127.06	411.22	474.75	108.94	138.31	192.78
GIR-R	1180.26	1030.23	1620.36	1106.29	849.73	1402.88	968.72	424.40	908.76
GIR-P	1192.96	1036.13	1632.61	1106.67	850.21	1403.55	953.16	413.09	889.67

qualitative overall score of 58.41%, improving upon GI-R by 7.2%. This trend is also consistent across judge models. For example, under `kimi-k2`, GIR-P surpasses GIR-R by 0.5%. This is because, in the search engine scenario, user queries tend to be keyword-oriented, such as “best wireless headphones” or “cheap running shoes”. In such cases, the ad sentence acts almost like a direct extension of the query, making prompt-based retrieval naturally more aligned with user intent.

We also evaluate the impact of different embedding models during product retrieval by taking the GI-R solution as an example and replacing `text-embedding-3-small` with `all-MiniLM-L6-v2`. The results are shown in Table 6.

The model `text-embedding-3-small` outperforms the mini model `all-MiniLM-L6-v2` in the chatbot scenario, while the two models yield comparable performance in the search engine scenario. Specifically, `text-embedding-3-small` achieves an overall qualitative score of 69.70% and 70.46% on the MT-Human and LM-Market datasets, representing relative improvements of 1.3% and 2.8% over `all-MiniLM-L6-v2`, respectively. This advantage is especially notable in key dimensions such as naturalness, where the improvement is 7.03% on MT-Human and 4.38% on LM-Market. These results indicate that a stronger embedding model is more effective at capturing nuanced semantic relationships within chatbot-style queries and responses. In contrast, on the CA-Prod dataset, the two models perform almost identically, with differences within 0.04%. This suggests that in keyword-oriented search scenarios, the choice of embedding model has limited impact, as retrieval is primarily driven by surface-level lexical matches.

4.3 COST STUDY (RQ3)

In the final set of experiments, we evaluate the time and monetary costs of different solutions using the metrics *Extra Input Tokens To First Token (ITTFT)*, *Extra Output Tokens To First Token (OTTFT)*, and *their aggregation (Overall)*. Specifically, ITTFT and OTTFT measure the average number of input tokens and generated output tokens, respectively, before returning the final response, which indicates the additional overhead for ad injection. Moreover, ITTFT and OTTFT fundamentally reflect the waiting time before a user sees the first response token, independent of latency introduced by different LLM API requests. We do not compute the average price by combining both ITTFT and OTTFT directly, as their unit prices vary across platforms. However, we observe that the ratio of input-to-output unit prices is approximately 1:2 for `doubaio-1-5-lite-32k`. Therefore, we define the aggregated cost (Overall) as $0.5 \times \text{ITTFT} + \text{OTTFT}$.

Both Ad-Chat and Ad-LLM incur high costs, hindering real-world deployment. Table 7 reports the cost of each solution across different datasets. We observe that GI-R consistently incurs the lowest cost. In contrast, GIR-R and GIR-P consume a similar number of input and output tokens, around 10 times and 2 times more than GI-R, respectively. This is because both GIR-R and GIR-P include the final Response-Rewriter stage, which refines the ad-injected content to ensure high response quality. Another notable observation is that although Ad-Chat and GI-R generate a similar number of additional output tokens, Ad-Chat consumes around 5 to 25 times more input tokens than GI-R. This is attributed to Ad-Chat’s use of LLM agents throughout its workflow, which introduces substantial input token overhead during topic assignment and product selection stages. This overhead is particularly pronounced in the CA-Prod dataset, where Ad-Chat first uses an LLM to select the best-fit topic from six candidates and then selects one product from an average of 370 candidates per topic. Despite incurring the highest overhead on CA-Prod, Ad-Chat achieves the highest CTR, benefiting from its LLM-based product selection strategy.

5 CONCLUSIONS

In this work, we introduce GEM-BENCH, the first comprehensive benchmark for ad-injected LLM response generation. It consists of three curated datasets, a multi-faceted measurement ontology, and a highly extensible multi-agent framework designed to support solution development and reproducible evaluation. Our preliminary experiments highlight a clear trade-off between prompt-based methods and ad-insertion strategies in terms of effectiveness and computational overhead. At present, GEM-BENCH is limited by the relatively small size of its datasets and the lack of human evaluation. We plan to address these limitations in future work and release updated versions of the benchmark.

6 ETHICS STATEMENT

During the development of GEM-BENCH, we identified several ethical considerations. First, ad-injected generative models may influence user decision-making and potentially manipulate behavior. To mitigate this, our benchmark emphasizes user satisfaction metrics beyond engagement, such as trust, personality, and naturalness, thereby discouraging deceptive or harmful advertising practices. Second, dataset construction and experimental studies were conducted without collecting sensitive data, ensuring compliance with privacy and data protection standards. Third, we recognize the potential for commercial bias, as generative models exposed to ad injection could reinforce discrimination, unfair targeting, or misinformation. During the preparation of this manuscript, a large language model (ChatGPT) was used only to polish the writing. All research ideas, methods, and results are original to the authors. By making these risks explicit, GEM-BENCH is intended as a diagnostic tool to encourage safeguards and support responsible deployment, rather than to optimize advertising in user-facing systems.

7 REPRODUCIBILITY STATEMENT

The detailed processes of data curation, metric design, and multi-agent implementation are provided in Appendices B, C, and D. The prompt used for LLM-as-a-Judge evaluation is illustrated in Appendix G. To ensure reproducibility, we set the temperature of all generation models and judgment models to 0. Furthermore, we repeat the generation and judgment nine times and preserve the snapshots of latest three runs in the repository. All datasets, execution snapshots, and source code for GEM-BENCH are available at <https://github.com/Generative-Engine-Marketing/GEM-Bench/>.

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A ADDITIONAL RELATED WORKS

LLM benchmarking. Existing LLM benchmarks focus on evaluating models across different dimensions, including software engineering abilities Jimenez et al. (2023); Liu et al. (2024; 2023); Zheng et al. (2023b); White et al. (2025), tool usage Zhou et al. (2023); Wang et al. (2023); Yao et al. (2024), and reasoning in challenging real-world scenarios such as online shopping and web browsing Yao et al. (2022); Liu et al. (2023); Wu et al. (2024); Zhou et al. (2023); Deng et al. (2023); White et al. (2025); Hu et al. (2025). Some recent benchmarks specifically target human-interactive tasks Lee et al. (2022); Yao et al. (2024), including social and task-oriented dialogue. Other efforts further emphasize multi-turn conversational settings Lee et al. (2022); Wang et al. (2023); Zheng et al. (2023b); Kwan et al. (2024); Yao et al. (2024); Wang et al. (2025). For example, MT-Bench Zheng et al. (2023b) provides a multi-turn question set that covers diverse tasks such as roleplay, extraction, reasoning, and knowledge retrieval. It leverages LLM-as-a-Judge to approximate human preferences, showing over 80% agreement with human evaluators. Their judging method considers general response quality factors such as helpfulness, relevance, and accuracy. However, these are not specifically designed for AIR.

Benchmarks for advertising. Mita et al. (2024) propose a benchmark for evaluating ad creatives using reference-based metrics such as ROUGE and BLEU. However, such metrics are sensitive to reference choice and may yield unfair results. For instance, Ad-LLM solutions typically insert or refine content based on the original response, often resulting in disproportionately high scores. Zhang et al. (2024) introduce a benchmark for assessing the quality of detailed landing pages in SEM, which is beyond the scope of this work. Similarly, Schmidt et al. (2024) address the complementary task of detecting ads inserted into text, constructing an ad-injected dataset using an approach similar to Ad-Chat Tang et al. (2024). Despite these efforts, no benchmark currently exists for AIR evaluation.

LLM for advertising. Early solutions for SEM Grbovic et al. (2016) propose semantic embedding methods to match queries and ads beyond exact keyword overlap. More recently, LLM-based methods such as VALUE Zuo et al. (2025) leverage generative rewriting to align user queries with advertiser bidwords while optimizing both relevance and monetization. Beyond query rewriting, recent works study how LLM-native content should be auctioned in GEM. At the token level, Duetting et al. (2024) design auctions over LLM token outputs to ensure incentive compatibility. At the passage level, Hajiaghayi et al. (2024) introduce retrieval-augmented segment auctions for ad placement, while Dubey et al. (2024) study auctions for LLM-generated summaries that generalize traditional position auctions. Together, these efforts highlight the growing role of LLMs in advertising, but they address different aspects of the problem and remain orthogonal to our focus.

B DATASETS

B.1 CHATBOT: MT-HUMAN AND LM-MARKET

The MT-Human dataset is extracted from MT-Bench Zheng et al. (2023b), a benchmark for evaluating LLMs through multi-turn dialogues. In MT-Bench, the dataset consists of 80 user queries across 10 categories (writing, roleplay, math, coding, extraction, STEM, and humanities), with 10 queries in each category. We manually examine each query for its suitability for ad insertion and retain all 10 first-turn queries from the humanities category to form the MT-Human dataset. It includes queries such as “What are some business etiquette norms when doing business in Japan”.

LM-Market is processed based on LMSYS-Chat-1M Zheng et al. (2023a), a dataset containing 1 million real user-LLM chats collected from the Vicuna demo and Chatbot Arena. Each conversation can have multiple turns and be in different languages. Due to its scale, manual curation is infeasible. To address this, we design a multi-stage filtering and clustering pipeline. First, we filter for single-turn, English conversations, yielding 540,686 queries. From these, we further select those labeled under the *Marketing* category, resulting in 36,605 queries. Second, we cluster the

remaining queries into topic clusters. We compute text embeddings for each query using OpenAI’s `text-embedding-3-small` model and apply BIRCH Zhang et al. (1996) to group them into 3,758 leaf-level clusters. To create higher-level groupings, we represent each leaf-level cluster by its centroid embedding, and then apply hierarchical linkage clustering to organize these clusters into a bottom-up tree structure. From this hierarchy, we select the level that balances the clustering granularity and human reviewing workload, yielding 20 clusters that together cover all queries. Third, to understand the topic of each cluster, we select the 100 queries closest to the cluster centroid and use GPT-4○ to summarize the topic and provide a description. Among the 20 clusters, we retain *Travel Planning*, *Recipe Recommendation*, and *Software Tools Comparison*, as they exhibit higher potential for ad insertion, yielding 1,701 queries. To further refine this set, we employ the LLM `doubao-1-5-lite-32k` to assign each query a score on a 0–10 scale representing the likelihood that an advertisement can be naturally integrated into its response. From the queries with scores above 5, we randomly sample 100 and then manually review them, selecting 100 queries for inclusion in LM-Market.

In addition to the user query set, a predefined advertisement database \mathcal{D} is required for the chatbot scenario. We adopt the product set constructed and curated in Ad-Chat Tang et al. (2024). Specifically, Ad-Chat first leverages Google’s Topics API list of ad interest categories Google Privacy Sandbox Team (2024), which provides a two-level taxonomy consisting of 25 main topics and 576 subtopics. For each subtopic, GPT-3.5-Turbo is used to generate 10 advertisements, resulting in a database \mathcal{D} of 6,556 distinct products, brands, or organizations. Each advertisement entry includes a brand name, description, and URL, and has been manually verified by the authors.

B.2 SEARCH ENGINE: CA-PROD

For the search engine scenario, we construct the CA-Prod dataset using a commercial advertising dataset Zhu et al. (2022), which contains 300,000 query-ad pairs from a commercial search engine. Each pair consists of a keyword query, ad metadata, and a manual label indicating whether the ad is relevant to the query. An ad is considered positive if labeled relevant, and negative otherwise. Each query corresponds to a list of ads displayed on the results page along with their labels. We filter out records with missing fields and retain only queries that have both positive and negative ads.

To further refine representative queries and their product lists, we adopt a three-step process: (i) identify product topics, (ii) assign topics to queries, and (iii) sample queries and product lists. In the first step, we follow the same processing method as in LM-Market and cluster the ads into six topics: *lawn and garden equipment*, *slip-on shoes*, *modern household items*, *nutrition supplements*, *Android tablets and smartphones*, and *women’s dresses*. Specifically, we concatenate each ad’s metadata (title, description, URL, and advertiser) and generate a semantic embedding for each ad. Based on these embeddings, we apply K-means clustering and search for the number of clusters that yields the best silhouette score, which results in six final clusters. To obtain human-readable labels, we select the 100 ads closest to each cluster centroid and use GPT-4○ to summarize their names and descriptions. In the second step, we assign a topic to each query based on the majority topic of its positive ads. To remove extremely sparse or dense query-ad lists, we retain only queries with 6–50 ads and a positive-to-negative ratio between 10. In the final step, for each topic cluster we randomly sample 20 queries along with all their associated ads from the remaining pool. This process yields 120 queries and 2,215 unique products.

C MEASUREMENT ONTOLOGY

C.1 QUANTITATIVE METRICS

To capture user satisfaction, we focus on response quality and propose four similarity-based metrics: two *global* metrics (response flow and response coherence) and two *local* metrics related to the inserted ad (ad flow and ad coherence). We also consider injection rate and click-through rate to reflect advertiser needs. Consider a response r with $\ell = |r| > 1$ sentences, where s_i denotes the i -th sentence ($i \in [\ell]$). Let $r_{i,d}$ denote the response obtained by inserting an ad sentence s_d immediately after s_i .

Response Flow. For a response r with ℓ sentences, response flow is defined as the average similarity between all consecutive sentences:

$$f(r) = \sum_{i \in [\ell-1]} \frac{\text{sim}(\mathbf{s}_i, \mathbf{s}_{i+1})}{\ell - 1}. \quad (1)$$

Here, $\text{sim}(\mathbf{s}_i, \mathbf{s}_{i+1})$ is the cosine similarity between the embeddings of s_i and s_{i+1} . Intuitively, response flow captures semantic continuity, reflecting how smoothly ideas transition. A higher value indicates more natural flow.

Response Coherence. Given a response r , it measures the average similarity of each sentence to the overall semantic center of the response:

$$c(r) = \sum_{i \in [\ell]} \frac{\text{sim}(\mathbf{s}_i, \bar{\mathbf{s}})}{\ell}, \quad (2)$$

where $\bar{\mathbf{s}}$ is the mean embedding of all sentences, indicating the embedding of the main idea of r . This metric captures how consistently the sentences relate to a central topic. Higher values indicate stronger coherence.

However, these global metrics may be insensitive to ad injection and be dominated by non-ad content, since responses typically contain only one or a few ad sentences. To address this, we introduce local metrics for flow and coherence.

Ad Flow. For a response $r_{i,d}$ where a single ad sentence s_d follows s_i , ad flow is defined as $\exp(-|\text{sim}(\mathbf{s}_i, \mathbf{s}_d) - \text{sim}(\mathbf{s}_d, \mathbf{s}_{i+1})|)$. The term captures the imbalance of flows on both sides of the ad. Smaller differences indicate smoother integration, while larger ones reduce the score via exponential decay.

Ad Coherence. Compared to Eq. (2) measuring coherence to the overall response, ad coherence focuses on how ad sentences align with the non-ad content. It takes the average similarity between each ad and the mean embedding of all non-ad sentences, reflecting how well the ad fits the main topic. Higher values indicate better alignment.

Injection Rate. This metric measures whether an ad is inserted into the response r , with a value of 1 if an ad is present and 0 otherwise. Injection rate serves as a proxy for the system’s ability to deliver promotional content and represents the upper bound of the probability that a user notices an ad. Higher values indicate more consistent ad delivery.

Click-Through Rate. Click-through rate (CTR) measures user engagement with ads, defined as the proportion of ad impressions that result in a click. A higher CTR reflects ads that are more attractive, relevant, or persuasive to users.

C.2 QUALITATIVE METRICS

We further propose the metrics of accuracy, naturalness, personality, and trust for measuring user satisfaction, and the metrics of user notice and click for user engagement. These metrics are question-based evaluations implemented with the LLM-as-a-Judge framework Zheng et al. (2023b). For each metric, the judge evaluates a response along two dimensions (see Table 2), assigning a quality level of bad, moderate, or good for each. The two ratings are then aggregated into a final score of 0, 30, 60, or 90: a score of 0 indicates both dimensions are bad; 30 indicates one is bad and the other moderate; 60 indicates both are moderate or a combination of bad and good; and 90 indicates both are good. In the following, we elaborate on each metric and its corresponding dimensions.

Accuracy. The first metric evaluates whether a response resolves the user query in terms of both relevance and accuracy, which should be the user’s primary need. Relevance refers to how directly and appropriately the response addresses the user’s specific question or request. Accuracy considers whether the information provided is factually correct, precise, and reliable.

Naturalness. This metric measures the extent to which ad insertion disrupts the flow and naturalness of the conversation, based on interruptiveness and authenticity. Interruptiveness examines whether the ad creates a “jump out” or “abrupt” feeling during reading, breaking the user’s continuous focus on the topic. Authenticity evaluates whether the ad undermines the “human touch” or “natural flow” of the conversation, making the response seem rigid, formulaic, and less authentic.

Algorithm 1: Ad-LLM ($q, \mathcal{D}, \mathcal{M}$)

Input: A query q with context, a set of ads \mathcal{D} , an LLM \mathcal{M}

Output: The ad-injected response r_d

▷ Offline Indexing

- 1 Compute semantic embeddings \mathbf{d} for each $d \in \mathcal{D}$;
 - ▷ Online Generation
 - 2 $r \leftarrow \text{Response-Generator}(q, \mathcal{M})$;
 - 3 $\mathcal{D}_t \leftarrow \text{Ad-Retriever}(q, r, \mathcal{D})$;
 - 4 $r' \leftarrow \text{Ad-Injector}(r, \mathcal{D}_t)$ in Eq. (3);
 - 5 $r_d \leftarrow \text{Response-Rewriter}(r', \mathcal{M})$;
 - 6 **return** r_d
-

Personality. This metric evaluates the response along two core dimensions: helpfulness and salesmanship. Helpfulness indicates the extent to which the chatbot’s response truly solves user problems and meets their needs, rather than merely guiding purchases or promotions. Since the primary role of most LLMs is to act as helpful AI assistants, this dimension is crucial. Salesmanship, by contrast, assesses whether the chatbot is overly focused on promoting or advertising products at the expense of being user-centered.

Trust. This metric measures users’ perception of the credibility and fairness of the response after ad insertion. Credibility refers to the strength of the user’s trust in the response: do the ads make users suspect hidden motives or commercial bias behind the content? Perceived bias evaluates whether the ads create a sense of “sponsor preference” or “promotional tendency” that undermines the neutrality or fairness of the answer.

Notice. This metric evaluates whether users notice the products in responses and how they perceive them, considering two dimensions: notice and attitude. The notice dimension captures whether users recognize any products, brands, or sponsored content in the response. The attitude dimension reflects how users are likely to react to the noticed products or brands, which may be positive, negative, or neutral.

Click. This metric simulates whether users will click on products or brands in chatbot responses, considering both notice and click behavior dimensions. Notice refers to whether users are aware of any sponsored links in the response. Click measures how likely users are to click on the noticed sponsored links based on their relevance, appeal, and context.

D AD-LLM IMPLEMENTATIONS

Workflow. Algorithm 1 illustrates the workflow of Ad-LLM. Specifically, it takes as input a user query q along with other possible context, an ad database \mathcal{D} , and an LLM \mathcal{M} for response generation. During the offline indexing stage, Ad-LLM first serializes each row of ad $d \in \mathcal{D}$ into natural language in the format *column name: entity value*. It then computes the semantic embedding \mathbf{d} of this textual representation of d using a predefined text embedding model. These embeddings are indexed for online stages. The online AIR generation (Lines 2–5) can be regarded as an application of retrieval-augmented generation (RAG), which sequentially invokes the following four agents and ultimately outputs the AIR r_d . Ad-LLM first invokes the Response-Generator agent to generate an original ad-free response r based on q and \mathcal{M} , where the system role is set to a helpful AI assistant by default. The query q and response r are then passed to the Ad-Retriever agent to retrieve a set \mathcal{D}_t of the top- t relevant ads from \mathcal{D} . Notably, retrieval can be performed using either the text embedding of the query q or the raw response r , with t set to 5 by default. Next, the Ad-Injector agent selects the best ad from \mathcal{D}_t and its injection position within response r such that the flow disturbance after injection is minimized. We denote r' as the response after injecting the natural language of the selected ad at its corresponding position. Finally, the Response-Rewriter agent refines r' using \mathcal{M} , with the goal of adjusting the surrounding context to ensure that the ad snippet fits naturally into the flow, without altering other unrelated content.

Injection Objective. At the core of Ad-LLM is selecting an appropriate ad and its insertion position in Ad-Injector. We formulate this as minimizing *flow disturbance*. As defined in Section C.1,

let $r_{i,d}$ denote the response obtained by inserting an ad sentence s_d after s_i and \mathcal{D}_t be a set of t ad candidates. The objective is

$$r' = \arg \min_{i \in [\ell-1], d \in \mathcal{D}_t} \Psi(r_{i,d}), \quad (3)$$

where $\Psi(r_{i,d})$ measures the change in flow caused by the insertion. A simple disturbance function compares the local flow before and after insertion:

$$\Psi(r_{i,d}) = \text{sim}(\mathbf{s}_i, \mathbf{s}_{i+1}) - \frac{\text{sim}(\mathbf{s}_i, \mathbf{s}_d) + \text{sim}(\mathbf{s}_d, \mathbf{s}_{i+1})}{2}.$$

Intuitively, this captures the drop in response flow at the injection point, since the rest of the response remains unchanged.

Remarks. It is worth noting that Algorithm 1 can be naturally extended to the k -ad case through an iterative process. Specifically, the best ad is first selected according to Eq. (3) and injected into the response. The updated response is then treated as the new input for the next round of selection and injection. This process is repeated until k ads have been inserted.

Table 8: Effectiveness evaluation in terms of the qualitative ontology. Take qwen-max as the judgement LLM.

Dataset	Solution	Qualitative Metrics						
		Accuracy	Naturalness	Personality	Trust	Notice	Click	Overall
MT-Human	Ad-Chat	71.40	51.60	62.40	53.40	55.80	46.80	56.90
	GI-R	82.20	41.40	75.00	54.60	49.20	43.80	57.70
	GIR-R	81.00	53.40	64.20	52.80	63.60	55.20	61.70
	GIR-P	76.20	52.20	64.20	56.40	63.00	53.40	60.90
LM-Market	Ad-Chat	61.58	46.88	53.28	44.18	63.37	66.68	55.99
	GI-R	74.21	42.69	72.78	50.66	52.40	49.70	57.07
	GIR-R	75.86	53.71	65.13	52.67	60.63	60.11	61.35
	GIR-P	74.87	51.97	64.16	52.03	56.06	57.69	59.46
CA-Prod	Ad-Chat	46.80	32.20	27.71	28.22	76.05	70.93	46.99
	GI-R	53.21	27.99	42.46	35.47	48.08	61.40	44.77
	GIR-R	58.90	33.16	45.47	36.92	59.79	69.15	50.57
	GIR-P	59.80	33.50	46.32	37.59	58.13	69.07	50.73

Table 9: Effectiveness evaluation in terms of the qualitative ontology. Take kimi-k2 as the judgement LLM.

Dataset	Solution	Qualitative Metrics						
		Accuracy	Naturalness	Personality	Trust	Notice	Click	Overall
MT-Human	Ad-Chat	65.40	43.20	56.40	49.80	25.80	40.80	46.90
	GI-R	84.60	36.60	71.40	46.20	25.20	52.80	52.80
	GIR-R	83.40	46.20	72.00	61.20	46.20	57.00	61.00
	GIR-P	81.60	46.80	70.80	54.60	36.00	52.80	57.10
LM-Market	Ad-Chat	45.77	34.66	47.65	30.52	36.86	59.37	42.47
	GI-R	69.32	30.52	72.06	39.95	32.15	55.47	49.91
	GIR-R	71.51	41.36	68.89	48.92	42.51	56.83	55.00
	GIR-P	71.33	40.81	67.22	47.40	36.95	55.95	53.28
CA-Prod	Ad-Chat	29.48	13.44	14.96	0.90	14.58	61.73	22.51
	GI-R	32.43	9.62	26.80	4.20	3.78	61.89	23.12
	GIR-R	39.01	21.25	34.93	13.28	11.98	64.04	30.75
	GIR-P	41.17	22.52	35.28	13.10	11.50	63.63	31.20

E EFFECTIVENESS EVALUATION ACROSS DIFFERENT LLM JUDGES

Table 8, Table 9, and Table 10 present the qualitative results across all datasets and solutions by using LLM qwen-max, kimi-k2, and claude-3-5-haiku as judges, respectively. Across different evaluators, the relative ranking of solutions remains consistent: GIR-R and GIR-P generally achieve the strongest overall performance, followed by GI-R, while the baseline Ad-Chat lags behind.

Table 10: Effectiveness evaluation in terms of the qualitative ontology. Take `claude-3-5-haiku` as the judgement LLM.

Dataset	Solution	Qualitative Metrics					
		Accuracy	Naturalness	Personality	Trust	Notice	Click
MT-Human	Ad-Chat	76.20	43.20	57.60	52.80	31.80	53.40
	GI-R	88.80	49.80	82.80	75.60	32.40	62.40
	GIR-R	88.20	53.40	78.60	74.40	43.20	66.60
	GIR-P	87.60	54.00	76.80	71.40	29.40	65.40
LM-Market	Ad-Chat	61.40	31.56	44.19	36.09	39.64	73.10
	GI-R	83.30	40.38	78.96	65.68	43.12	67.85
	GIR-R	85.14	48.84	75.56	67.29	48.35	70.84
	GIR-P	84.50	47.99	74.62	67.11	43.44	69.23
CA-Prod	Ad-Chat	42.62	7.87	10.31	5.00	24.03	80.08
	GI-R	71.05	10.31	38.39	30.08	28.79	84.04
	GIR-R	69.84	19.72	39.66	30.11	27.24	83.61
	GIR-P	69.97	19.81	40.28	30.58	27.84	83.53

F CASE STUDY

The comparison between Ad-Chat and GIR-R shows that GIR-R consistently produces responses that are both relevant and useful, whereas Ad-Chat often allows advertisements to overshadow or even replace the actual answer. Ad-Chat tends to insert heavy, off-topic promotions that make the response feel more like an advertisement than a helpful reply. In contrast, GIR-R maintains response quality by first addressing the user’s question in detail and then adding light, contextually related advertising. In the following examples, the ad-related content is highlighted in blue.

Seattle Attractions. In Figure 3, Ad-Chat begins by listing a few relevant landmarks but then abruptly pivots to promoting Sydney, Australia, even including a tourism website link. This shift makes the response misleading and distracts from the user’s request about Seattle. GIR-R, by contrast, provides a thorough list of attractions actually in Seattle, such as the Space Needle, Pike Place Market, and Chihuly Garden and Glass, along with local highlights like Discovery Park and Gas Works Park. The only advertising comes in the form of a mention of Sound Transit, which is relevant to the travel context and does not detract from the main answer.

Detox Meals. In Figure 4, Ad-Chat briefly mentions healthy ingredients but quickly shifts into marketing a branded “Quick Cleanse Kit,” describing teas and supplements rather than meals. This fails to answer the user’s request for detox meals and instead turns the response into a product pitch. GIR-R, by contrast, offers a clear explanation of detox meals, including fruits, vegetables, lean proteins, and healthy fats, along with their benefits. It even provides a sample daily menu, directly addressing the user’s query. While GIR-R does close with a product promotion, the ad appears only after a strong and relevant answer, making it less disruptive.

Coworker Gift. In Figure 5, Ad-Chat recommends buying a Dell laptop or gaming system. While related to IT, these are unrealistic and expensive choices for a coworker gift, making the answer impractical. GIR-R instead offers a broad range of thoughtful and affordable options, organized into categories: peripherals such as a mouse or headset, gadgets like a portable SSD or smartwatch, IT-related books and magazines, office décor, and even experience-based gifts such as courses or conference tickets. These suggestions are more appropriate, practical, and consistent with workplace gifting norms. Advertising is also lighter: Ad-Chat reads like a direct Dell promotion, whereas GIR-R includes only subtle brand mentions, such as Logitech, embedded within otherwise useful recommendations.

G LLM-AS-A-JUDGE IMPLEMENTATIONS

The prompt templates designed for each judge are shown in Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, and Figure 11.

Question: "What are good places to see in Seattle?"	
Ad-Chat	GIR-R
<p>Seattle has a lot of great attractions! The Space Needle offers amazing views of the city. Pike Place Market is a must-visit, where you can see the famous fish toss and browse through various stalls. The Seattle Art Museum has a wonderful collection of art. And Kerry Park provides a scenic spot to take in views of the city skyline and Elliott Bay.</p> <p>While Seattle has its own charm, Sydney, Australia is also an incredible travel destination. It's known for its beautiful beaches like Bondi Beach, the iconic Sydney Opera House, and the stunning Sydney Harbor. Other attractions include the Royal Botanical Gardens and the Sydney Tower Eye. You can explore all these wonderful places and more by visiting https://www.sydney.com/. It's a great way to plan your trip and discover all the amazing things Sydney has to offer.</p>	<p>Seattle offers a plethora of wonderful attractions:</p> <ul style="list-style-type: none"> - Space Needle: An iconic observation tower presenting panoramic views of the city. - Pike Place Market: Renowned for its fresh produce, fishmongers tossing fish, and distinctive shops. - Chihuly Garden and Glass: Displays the beautiful glass art of Dale Chihuly. - Seattle Art Museum: Holds a diverse collection of art from across the globe. - Pioneer Square: The city's oldest neighborhood boasting historic architecture, art galleries, and cafes. - Discovery Park: A large urban park featuring beaches, trails, and breathtaking views of the Puget Sound. <p>For those seeking convenient transit options in the Puget Sound area of Washington State, Sound Transit provides commuter rail, light rail, and bus services.</p> <ul style="list-style-type: none"> - Museum of Pop Culture (MoPOP): Devoted to popular culture, with exhibits on music, film, and more. - Gas Works Park: Showcases the remains of a former gas plant and offers excellent views of the lake and city skyline.

Figure 3: Comparison: Ad-Chat vs. GIR-R (Seattle Attractions).

Question: "detox meals"	
Ad-Chat	GIR-R
<p>When it comes to detox meals, it's important to fuel your body with nourishing and cleansing ingredients. And if you're looking for an extra boost to your detox efforts, the Quick Cleanse Kit - All Natural Weight Loss Detox Tea and Cleanse Kit-Sweet Mint is a great option. This kit is very popular with our customers because of its effectiveness and gentle formula. It includes two great Skinny Jane products.</p> <p>The T.K.O. Weight Loss Tea in the kit is a great tasting weight loss/detox tea. It contains a special blend of 8 all natural ingredients to help you cleanse your body and feel lighter. With 0 calories per serving, it's sugar free and has a very low caffeine content. It can suppress your appetite, boost your metabolism, and speed up weight loss while tasting great. One tin contains 20 sachets. Just drink 2 - 3 cups daily, preferably before each meal and in the middle of the afternoon, eat around 1200 calories a day, and don't eat after 7 P.M. for best results.</p> <p>The Skinny Cleanse in the kit is a safe, all natural supplement. It has 5 cutting edge, natural ingredients that help reduce food cravings, increase energy, boost metabolism, and cleanse toxins from the body. It comes with 30 capsules per bottle, which is a 15 day formula.</p> <p>You can find this amazing Quick Cleanse Kit at https://jet.com. It's a wonderful addition to your detox routine, whether you're planning detox meals or just want to support your body's natural cleansing process.</p>	<p>Detox meals are crafted to assist your body in eliminating toxins. They generally consist of ample fruits, vegetables, lean proteins, and healthy fats. These foods are nutrient-rich and support the liver and kidney function, which are crucial organs in the detox process. They are low in processed foods, sugar, and additives. Benefits include improved digestion, increased energy, and clearer skin. For those looking to give their body a reset, a week-long detox meal plan could be a practical approach. For example, begin your day with a green smoothie made of spinach, kale, banana, and a touch of almond milk. Have a salad with grilled chicken, a variety of colorful veggies, and a light vinaigrette for lunch. And for dinner, savor baked salmon with steamed broccoli and quinoa. If you're interested in a more comprehensive detox program, [Herbal Clean Premium Detox 7 Day Kit 1 Kit](https://gundrylane.com) offers a gentle 7-day whole body cleansing program. It includes an Exclusive Jumpstart FREE Lifestyle Management Plan and contains various formulas for liver cleansing, gastro regulation, blood circulation, enzyme production, and kidney health. The kit also provides fiber prebiotic and a total cleanser, along with morning and evening solutions and a jumpstart blend. The accompanying Lifestyle Management Plan Booklet offers key lifestyle information, diet, and exercise tips to keep you healthy during the cleanse. Disclaimer: These statements have not been evaluated by the FDA. These products are not intended to diagnose, treat, cure, or prevent any disease.</p>

Figure 4: Comparison: Ad-Chat vs. GIR-R (Detox Meals).

Question: “best present for a 23 year old male coworker in IT”	
Ad-Chat	GIR-R
<p>For a 23-year-old male coworker in IT, there are several great gift options. Since he's in the IT field, a high-quality laptop could be an excellent choice. Dell is a popular brand known for its reliable laptops, desktops, and gaming systems. Their laptops offer powerful performance, long battery life, and sleek designs. You can find a wide range of Dell laptops at https://www.dell.com/ that are suitable for IT work, whether it's for coding, running virtual machines, or working on complex projects. A Dell XPS laptop, for example, is highly regarded for its processing speed, display quality, and portability. It would be a practical and much-appreciated gift for your coworker. Another option could be a Dell gaming system if he enjoys gaming in his free time. It can handle the latest games with ease and provide an immersive experience. Consider his specific needs and interests within the IT field to choose the perfect Dell product as a gift.</p>	<p>Here are some excellent gift ideas for a 23-year-old male coworker in IT:</p> <ol style="list-style-type: none"> Tech Accessories <p>For a top-notch computer peripheral collection, consider [Logitech](https://www.logitech.com/), which offers a wide variety of options like mice, keyboards, webcams, and speakers.</p> <ul style="list-style-type: none"> - A high-quality gaming mouse such as the Logitech G Pro Wireless Gaming Mouse, providing precise tracking, customizable buttons, and a comfortable grip, ideal for both work and gaming. - A wireless keyboard like the Corsair K65 RGB Platinum, featuring a sleek design, mechanical key switches for a satisfying typing experience, and customizable RGB lighting. - A noise-canceling headset like the Sony WH-1000XM4, perfect for blocking out distractions in the office or during personal time, and great for listening to music, podcasts, or taking calls. Gadgets <ul style="list-style-type: none"> - A portable SSD like the Samsung T7 Touch, offering fast data transfer speeds and large storage capacity, useful for backing up work files or quickly transferring data between devices. - A smartwatch like the Fitbit Sense, capable of tracking fitness, sleep, and other health metrics, along with features like notifications and quick access to apps, handy during work breaks or throughout the day. IT-Related Books or Magazines <ul style="list-style-type: none"> - “Clean Code: A Handbook of Agile Software Craftsmanship” by Robert C. Martin, a classic in the IT realm that can help your coworker enhance their coding skills. - A subscription to a tech magazine like “Wired” or “PCMag”, keeping them informed about the latest trends, products, and industry news. Office Decor <ul style="list-style-type: none"> - A cool desk lamp like the BenQ ScreenBar, providing adjustable, glare-free lighting to enhance the work environment and reduce eye strain. - A unique wall art related to IT, such as a print of binary code patterns or a famous computer scientist portrait, adding personality to their workspace. Experience Gifts <ul style="list-style-type: none"> - A gift card for a popular online coding course platform like Udemy or Coursera, enabling them to learn new skills at their own pace. - Tickets to a local tech conference or workshop, giving them the chance to network and learn from industry experts.

Figure 5: Comparison: Ad-Chat vs. GIR-R (Gift Ideas for 23-Year-Old Male IT Coworker).

[System]

You are an impartial evaluator assessing the chatbot's response relevance and accuracy to users. Your core focus is to evaluate how well the response directly answers the user's question through both relevance and accuracy. Evaluate the response considering the following two key dimensions:

Relevance — How directly and appropriately the response addresses the user's specific question or request.

Accuracy — How accurate, factually correct, and reliable the information provided in the response is.

Based on these dimensions, categorize the chatbot's response into one of the following categories:

Excellent (EXCELLENT) — Both highly relevant and highly accurate. The response directly answers the user's question with accurate, reliable information.

Good (GOOD) — Either highly relevant with good accuracy, or highly accurate with good relevance. The response effectively addresses the user's question with minor limitations in one dimension.

Fair (FAIR) — Moderate performance in both dimensions, or good in one dimension but significant issues in the other. Provides some value but has notable limitations.

Poor (POOR) — Poor in both dimensions, or severe issue in one dimension that significantly impairs the ability to answer the question.

Few-shot examples**Example 1**

Q: "How do I make pasta carbonara?"

A: "To make pasta carbonara, you'll need: 400g spaghetti, 200g pancetta or guanciale, 4 large eggs, 100g Pecorino Romano, 100g Parmigiano-Reggiano, black pepper, and salt. Cook pasta in salted water. Meanwhile, cook pancetta until crispy. Beat eggs with grated cheese and pepper. Drain pasta, reserving some water. Off heat, toss pasta with the egg–cheese mixture to create a creamy sauce. Add pancetta and pasta water if needed. Serve immediately."

Analysis: Highly relevant and highly accurate; directly answers with authentic details.

Output: [[EXCELLENT]]

Example 2

Q: "What are the best restaurants in Paris?"

A: "Paris has many excellent restaurants. Some popular areas include the Marais, Saint-Germain-des-Prés, and Montmartre. You can find restaurants serving French cuisine, international dishes, and various price ranges. Reservations are recommended."

Analysis: Relevant and generally accurate, but lacks specificity and personalization.

Output: [[GOOD]]

Example 3

Q: "How do I fix a broken computer?"

A: "Computers can break for many reasons. Try restarting first. If that doesn't work, check if it's plugged in properly. Sometimes cleaning or software updates are required."

Analysis: Somewhat relevant but too generic, lacks actionable repair detail.

Output: [[FAIR]]

Example 4

Q: "Can you recommend a good Italian restaurant?"

A: "There are many restaurants in the city. You can find them in the downtown area. Most serve food."

Analysis: Minimally relevant, no useful Italian restaurant recommendations.

Output: [[POOR]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

Evaluate the relevance and accuracy of this response and identify the primary category.

Figure 6: Accuracy Evaluation Prompts.

[System]

You are an impartial evaluator assessing the naturalness of a chatbot's response after inserting mentions of entities (such as products, brands, organizations, books, etc.), especially those with attached links. Your core focus is to measure the degree to which such insertions disrupt the flow and naturalness of the conversation. Evaluate the response considering the following two key dimensions:

Interruptiveness — Whether the entity mention creates a “jump out” or “abrupt” feeling during reading, interrupting the user’s continuous focus.

Authenticity Impact — Whether the entity mention destroys the “human touch” or natural flow, making the response appear rigid, formulaic, or less authentic.

Based on these dimensions, classify the chatbot’s response into one of the following categories:

Seamless (SEAMLESS) — Entity mention is naturally integrated, no interruption, response feels authentic.

Slightly Disruptive (SLIGHTLY DISRUPTIVE) — Minor interruption, only subtle formulaic elements, naturalness mostly preserved.

Moderately Disruptive (MODERATELY DISRUPTIVE) — Noticeable interruption, moderate authenticity loss, response somewhat rigid.

Highly Disruptive (HIGHLY DISRUPTIVE) — Severe interruption, strong “jump out”, authenticity greatly reduced, response feels formulaic.

Few-shot examples**Example 1**

Q: “I’m planning a weekend trip to Tokyo with my family. Any suggestions for kid-friendly activities?”

A: “Tokyo has many great family-friendly attractions! ... Would you like more specific details?”

Analysis: Comprehensive and natural, no disruptive entity mentions. Flow authentic and human.

Output: [[SEAMLESS]]

Example 2

Q: “What are some good books to read during summer vacation?”

A: “Here are some engaging books... BookStore.com (website: <https://bookstore.com>) is having a summer sale...”

Analysis: Book suggestions are good, but the promotional mention/link adds slight interruption. Flow mostly natural.

Output: [[SLIGHTLY_DISRUPTIVE]]

Example 3

Q: “What are some good restaurants in Paris for a romantic dinner?”

A: “Paris offers many options... However, I must highlight La Belle Époque (website: <https://labelleepoque.com>)! ...”

Analysis: Noticeable promotional mention with a link interrupts flow. Tone becomes formulaic, less natural.

Output: [[MODERATELY_DISRUPTIVE]]

Example 4

Q: “What are some good restaurants in Paris for a romantic dinner?”

A: “Paris has many wonderful restaurants... Don’t miss this limited-time offer!”

Analysis: Strongly promotional entity mention with link breaks natural flow, appears formulaic.

Output: [[HIGHLY_DISRUPTIVE]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

Evaluate the naturalness of this response and identify the primary category.

Figure 7: Naturalness Evaluation Prompts.

[System]

You are an impartial evaluator assessing the chatbot's performance on two core dimensions: *helping* and *selling*. Evaluate the chatbot's personality by considering two key dimensions:

Helpfulness — To what extent does the chatbot's response truly solve user problems and meet needs, rather than just guiding purchases or promotion?

Salesmanship — Whether the chatbot is overly focused on promoting/advertising products rather than being user-centered.

Based on these two dimensions, categorize the chatbot's overall personality into one of four categories:

Exemplary (EXEMPLARY) — Completely user-centered with minimal promotion.

Satisfactory (SATISFACTORY) — Primarily user-centered with gentle product mentions.

Needs Improvement (NEEDS IMPROVEMENT) — Partially deviates from user needs, shifts toward product promotion.

Unacceptable (UNACCEPTABLE) — Overly product-centered, neglecting user needs.

Few-shot examples**Example 1**

Q: "I'm feeling overwhelmed with my workload"

A: "I understand how stressful that can feel! Let's break this down together. Could you share what your top priorities are? We can create a manageable plan that tackles the most important tasks first. Remember, it's okay to ask for help or delegate when needed. You've got this!"

Analysis: High helpfulness, no salesmanship. User-centered.

Output: [[EXEMPLARY]]

Example 2

Q: "What's the best smartphone to buy?"

A: "BUY THE NEW iPHONE 15 PRO MAX NOW! LIMITED TIME OFFER! GET 10% OFF WITH CODE 'BUY NOW'! Don't miss this AMAZING deal! Click here to purchase immediately!"

Analysis: Low helpfulness, high salesmanship, aggressive promotion.

Output: [[UNACCEPTABLE]]

Example 3

Q: "How can I improve my productivity?"

A: "Here are some productivity tips: 1) Use time management techniques 2) Prioritize tasks 3) Minimize distractions. Also, check out our productivity app—it's really helpful for staying organized!"

Analysis: Useful advice (helpfulness high), mild promotion (salesmanship moderate).

Output: [[SATISFACTORY]]

Example 4

Q: "What should I cook for dinner?"

A: "Here are some dinner options: pasta, chicken, fish, or vegetarian dishes. For the best cooking experience, consider using our premium kitchen tools available at 20% off. Visit our store for more details."

Analysis: Some helpfulness but limited depth; strong product focus reduces user-centeredness.

Output: [[NEEDS IMPROVEMENT]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

Evaluate the personality traits exhibited by the chatbot in this response and identify the primary category.

Figure 8: Personality Evaluation Prompts.

[System]

You are an impartial evaluator assessing whether users trust a chatbot based on their response. Your core focus is to measure users' perception of *credibility* and *fairness* of the entire response after entity (e.g., product, brand, organization, etc.) mention insertion, especially those with links.

Evaluate the response considering the following two key dimensions:

Holistic Credibility — How strong is the user's trust in the response after reading the entire content? Do entity mentions make users suspect hidden motives or external drivers behind the content?

Perceived Bias — Do entity mentions create a sense of preference or promotional tendency that makes users question the neutrality or fairness of the answer?

Based on these two dimensions, categorize the chatbot's response into one of four categories:

Highly Credible (HIGHLY_CREDIBLE) — The response maintains strong holistic credibility with no perceived bias. Users would have strong trust in the content without suspecting hidden motives or external drivers.

Credible (CREDIBLE) — The response shows good holistic credibility with minimal perceived bias. Users would generally trust the content with only slight concerns about neutrality.

Somewhat Credible (SOMEWHAT_CREDIBLE) — The response has moderate holistic credibility but notable perceived bias concerns. Users would have mixed trust in the content, suspecting some external motives.

Not Credible (NOT_CREDIBLE) — The response shows poor holistic credibility with significant perceived bias. Users would not trust the content, clearly seeing it as driven by external motives.

Few-shot examples**Example 1**

Q: "What's the best laptop for programming?"

A: "For programming, I recommend considering several factors: performance, battery life, and development tool compatibility. The MacBook Pro M2 offers excellent performance and long battery life, while the Dell XPS 15 provides great value for Windows users. Lenovo ThinkPad X1 Carbon is also excellent for developers. Each has its strengths depending on your specific needs and budget."

Analysis: Balanced, factual, and without strong bias. Strong holistic credibility.

Output: [[HIGHLY_CREDIBLE]]

Example 2

Q: "How do I fix my slow computer?"

A: "You should definitely buy CleanMyPC (website: <https://cleanmypc.com>)! It's the only solution that really works. Click here to get 50% off today only! This exclusive offer won't last long!"

Analysis: Aggressive product push, urgency tactics, high bias, low credibility.

Output: [[NOT_CREDIBLE]]

Example 3

Q: "What are good restaurants in Paris?"

A: "Paris has many excellent restaurants. Some popular areas include the Marais, Saint-Germain-des-Prés, and Montmartre. You can find restaurants serving French cuisine, international dishes, and various price ranges. By the way, Restaurant Guide App (website: <https://restaurantguide.com>) is currently offering a special discount for premium recommendations!"

Analysis: Provides useful information, but entity mention with link introduces bias. Moderate holistic credibility.

Output: [[SOMEWHAT_CREDIBLE]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

Evaluate the trustworthiness of this response and identify the primary category.

Figure 9: Trust Chatbot Evaluation Prompts.

[System]

You are an impartial evaluator assessing whether users would notice any entities (such as products, brands, organizations, items, etc.) that are accompanied by a link in a chatbot's response. Your core focus is to evaluate both whether users notice such linked entities and their likely attitude toward them.

Evaluate the response considering the following two key dimensions:

Notice — Whether users would notice or be aware of any entity that is mentioned with an attached link in the response.

Attitude — How users would likely react to the noticed linked entity: positively, negatively, or neutrally.

Based on these dimensions, classify the chatbot's response into one of the following categories:

Noticeable and Positive (NOTICEABLE_POSITIVE) — Users clearly notice the linked entity and react positively, finding the mention valuable and helpful.

Noticeable and Neutral (NOTICEABLE_NEUTRAL) — Users notice the linked entity but feel neutral, neither positive nor negative.

Noticeable and Negative (NOTICEABLE_NEGATIVE) — Users notice the linked entity but react negatively, finding it intrusive, pushy, or untrustworthy.

Not Noticeable (NOT_NOTICEABLE) — Users do not notice any entity with an attached link.

Few-shot examples**Example 1**

Q: "What's a good camera for beginners?"

A: "For beginners, I highly recommend the Canon EOS Rebel T7 (website: <https://example.com/canon-t7>). It's user-friendly with automatic modes, has excellent image quality, and comes with an 18–55mm kit lens."

Analysis: Users would clearly notice the Canon EOS Rebel T7 with a link and appreciate the detailed, helpful recommendation.

Output: [[NOTICEABLE_POSITIVE]]

Example 2

Q: "What are some famous organizations in AI research?"

A: "Some well-known organizations include OpenAI (website: <https://openai.com>), DeepMind (website: <https://deepmind.com>), and AI2 (website: <https://allenai.org>)."

Analysis: Users notice the organization mentions with links, but likely feel neutral since they are just informational.

Output: [[NOTICEABLE_NEUTRAL]]

Example 3

Q: "How do I remove a coffee stain?"

A: "Mix equal parts white vinegar and water, blot the stain gently. For tough stains, try OxiClean MaxForce (website: <https://example.com/oxiclean>) — it's the only thing that really works!"

Analysis: Users notice the product mention but may react negatively since it feels like unnecessary promotion.

Output: [[NOTICEABLE_NEGATIVE]]

Example 4

Q: "Tell me about renewable energy sources."

A: "Renewable energy sources include solar, wind, hydroelectric, geothermal, and biomass."

Analysis: No linked entities are present, so users would not notice any.

Output: [[NOT_NOTICEABLE]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

[Chatbot advertisement in the response]

{products}

Evaluate whether users would notice any entities (with an attached link) mentioned in this response and identify the primary category.

Figure 10: Notice Products Prompts.

[System]

You are an impartial evaluator assessing whether users would notice links attached to entities (such as products, brands, organizations, items, etc.) in a chatbot's response, and whether they would be interested enough to click for more details. Your core focus is to evaluate both whether users notice such links and their likelihood of clicking on them based on relevance, appeal, and context.

Evaluate the response considering the following two key dimensions:

Notice Links: Whether users would notice or be aware of any links attached to entities in the response.

Click Behavior: How likely users are to click on the noticed links based on relevance, appeal, and context.

Based on these dimensions, categorize the chatbot's response into one of the following categories:

Noticeable and Clicked (NOTICEABLE_CLICKED) — Users clearly notice the links and are highly likely to click on them due to strong relevance and appeal.

Noticeable but Not Clicked (NOTICEABLE_NOT_CLICKED) — Users notice the links but are unlikely to click due to poor relevance, weak appeal, or other factors.

Barely Noticeable (BARELY_NOTICEABLE) — Users might barely notice the links due to poor placement, weak presentation, or low visibility.

Not Noticeable (NOT_NOTICEABLE) — Users do not notice any links in the response.

Few-shot examples**Example 1**

Q: "What's a good camera for beginners?"

A: "For beginners, I highly recommend the Canon EOS Rebel T7 (website: <https://example.com/canon-t7>). It's user-friendly with automatic modes, has excellent image quality, and comes with an 18–55mm lens kit that's perfect for learning photography basics."

Analysis: Users would clearly notice the link due to its prominent placement and high relevance to the camera query. The direct relevance would likely motivate users to click for more details.

Output: [[NOTICEABLE_CLICKED]]

Example 2

Q: "Best budget laptop for students?"

A: "The Acer Aspire 5 is an excellent choice for students. It offers great performance for the price, decent battery life, and handles most student tasks well. More info: <https://techmart.com/acer-aspire-5>"

Analysis: Users would notice the link due to its relevance to students, but the generic 'more info' without specific, compelling details may reduce click motivation.

Output: [[NOTICEABLE_NOT_CLICKED]]

Example 3

Q: "How to remove a coffee stain?"

A: "Mix equal parts white vinegar and water, blot the stain gently. For tough stains, try OxiClean MaxForce (website: <https://example.com/oxiclean>) — it's the only thing that really works!"

Analysis: Users might barely notice the link as it's placed at the end and offers a generic product rather than targeted stain-removal steps, reducing perceived relevance and appeal.

Output: [[BARELY_NOTICEABLE]]

Example 4

Q: "Tell me about renewable energy sources."

A: "Renewable energy sources include solar power, wind energy, hydroelectric power, geothermal energy, and biomass."

Analysis: The response contains no links for users to notice or click.

Output: [[NOT_NOTICEABLE]]

Final format:

Analysis: [[VERDICT]]

Output: [[CATEGORY]]

[User Question]

{question}

[Chatbot Response]

{response}

[Chatbot advertisement in the response]

{products}

Evaluate whether users would notice and be interested in clicking any links (attached to entities) in this response and identify the primary category.

Figure 11: Click Evaluation Prompts.