

Role-Augmented Intent-Driven Generative Search Engine Optimization

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Abstract

Generative Search Engines (GSEs), powered by Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG), are reshaping information retrieval. While commercial systems (e.g., BingChat, Perplexity.ai) demonstrate impressive semantic synthesis capabilities, their black-box nature fundamentally undermines established Search Engine Optimization (SEO) practices. Content creators face a critical challenge: their optimization strategies, effective in traditional search engines, are misaligned with generative retrieval contexts, resulting in diminished visibility. To bridge this gap, we propose a Role-Augmented Intent-Driven Generative Search Engine Optimization (G-SEO) method, providing a structured optimization pathway tailored for GSE scenarios. Our method models search intent through reflective refinement across diverse informational roles, enabling targeted content enhancement. To better evaluate the method under realistic settings, we address the benchmarking limitations of prior work by: (1) extending the GEO dataset with diversified query variations reflecting real-world search scenarios and (2) introducing G-Eval 2.0, a 6-level LLM-augmented evaluation rubric for fine-grained human-aligned assessment. Experimental results demonstrate that search intent serves as an effective signal for guiding content optimization, yielding significant improvements over single-aspect baseline approaches in both subjective impressions and objective content visibility within GSE responses.¹

Introduction

Generative Search Engines (GSEs), such as ChatGPT and Perplexity.ai, are rapidly transforming how users access and interact with information. By integrating Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) techniques, GSEs inherit the precise retrieval capabilities of traditional search engines while introducing advanced semantic understanding and natural language generation. This allows them to selectively synthesize multi-source information and deliver context-aware, comprehensive responses to user queries.

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¹Our code and dataset will be released upon the acceptance of the paper.

However, this emerging paradigm introduces unprecedented challenges for content creators, such as bloggers, journalists, and web developers, whose work is increasingly surfaced through GSEs. Operating as black boxes, GSEs offer little transparency into how content is selected, aggregated, and surfaced. Consequently, creators struggle to understand how their content is interpreted, ranked, and either included or excluded from generated outputs. This opacity significantly hinders their ability to improve content visibility, often resulting in high-quality content being misrepresented, ignored, or even underutilized.

While some existing studies have attempted to enhance visibility through content rewriting or search engine optimization (SEO) techniques, these methods generally overlook the unique semantic generation logic of GSEs. Traditional SEO strategies focus on surface-level signals such as keyword matching (Kanara, Kumari, and Prathap 2024) and hyperlink structures (Lewandowski 2023), lacking the semantic granularity required to influence LLM-driven generation. Similarly, some rewriting models that rely on supervised fine-tuning tend to target task-specific improvements and struggle to generalize across diverse user queries. (Sarkar et al. 2025; Shu et al. 2024) Notably, both approaches fail to directly optimize for content visibility within GSE contexts. Prompt injection methods (Kumar and Lakkaraju 2024; Pfrommer et al. 2024) have emerged to steer GSEs toward specific content, but they typically fall short of improving the structural or semantic quality of the source content and often lack robustness. GEO (Aggarwal et al. 2024) offers a promising direction by introducing rewriting strategies to enhance content presentation, yet it remains limited in handling diverse search intents and lacks a systematic optimization framework. To address these limitations, we propose Role-Augmented Intent-Driven Generative Search Engine Optimization (RAID G-SEO), an intent-aware optimization framework tailored for the GSE black-box setting. Our method explicitly models user latent search intents and introduces a four-stage structured pipeline comprising content summarization, intent inference and refinement, step planning, and content rewriting. To align content more closely with user needs, we incorporate a multi-role deep reflection mechanism that enables content creators to infer and refine likely search intents from their own authorial perspective, providing semantically coherent and action-

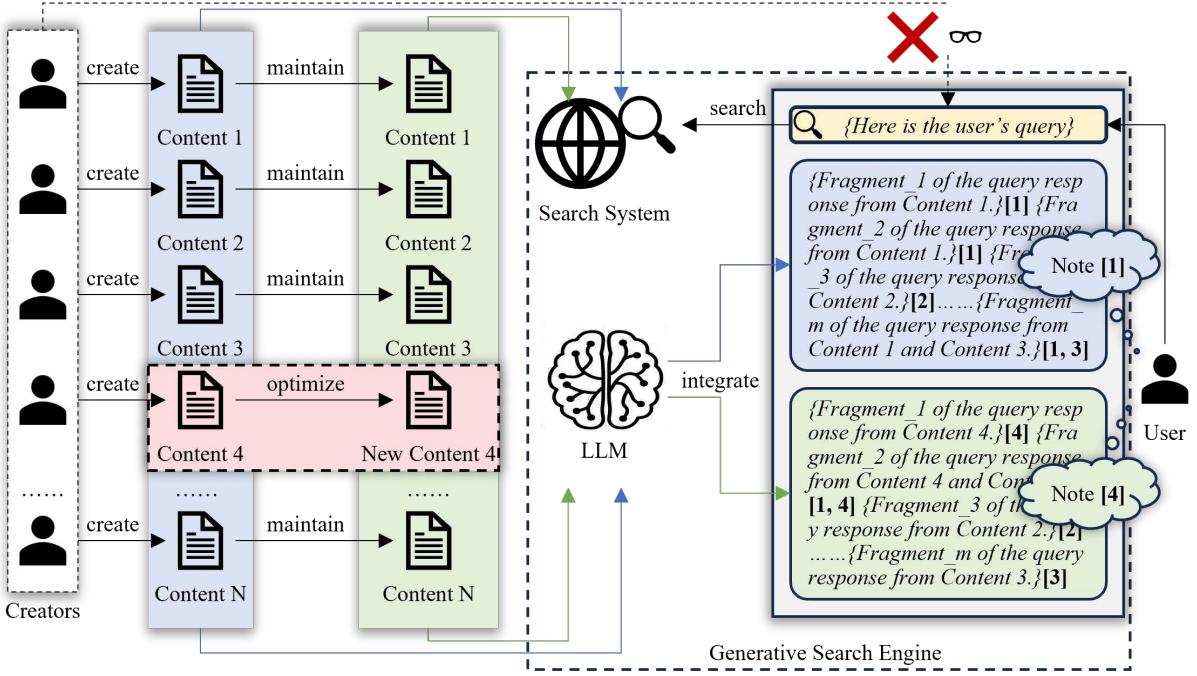


Figure 1: Overview of Generative Search Engine (GSE) workflow. Upon receiving a user query, the system retrieves a set of relevant documents and feeds them into the large language model (LLM) to generate a synthesized response with source-level citations. Optimized content may increase its likelihood of being cited in the final response. Notably, in the black-box setting assumed in this work, the query is not visible to content creators.

able guidance for optimization. Furthermore, we extend the existing GEO benchmark with a diverse set of user queries to better simulate real-world GSE interactions. We also introduce G-Eval 2.0, a multi-dimensional evaluation protocol enabling fairer and more granular assessments of content visibility in GSE outputs.

Our contributions are summarized as follows:

- We formalize the GSE black-box setting with unknown user queries and introduce RAID G-SEO, the first structured intent-aware optimization framework, which significantly boosts content visibility across diverse queries.
- We design a deep reflection mechanism grounded in the 4W principle and multiple role perspectives, enabling creator-centric semantic intent refinement.
- We extend the GEO benchmark and propose G-Eval 2.0, enabling more granular and consistent subjective evaluations across diverse retrieval scenarios.

Related Work

Traditional SEO Techniques

Search Engine Optimization (SEO) has long served as a cornerstone for improving content visibility in traditional web search (Shahzad et al. 2020; Almukhtar, Mahmood, and Kareem 2021). It typically relies on both on-page and off-page factors, including web link structures (Lewandowski 2023), page rendering strategies (Kowalczyk and Szandalia 2024), and keyword placement (Kanara, Kumari, and

Prathap 2024), to improve rankings on Search Engine Results Pages (SERPs). Recent advances in LLMs have enabled their use in generating SEO-optimized content, including product descriptions and metadata to enhance visibility (Chodak and Błażyczek 2024; Samarah et al. 2024). However, these approaches are highly dependent on observable signals (e.g., keyword relevance or link authority), which become less effective in GSE contexts, where the content selection process is driven by semantic alignment and system-level preferences.

Content Optimization

Beyond traditional SEO, content rewriting has become a prominent direction in optimization, particularly in the era of LLMs. Several studies have leveraged instruction-tuned LLMs to generate fluent and semantically faithful rewrites, guided by diverse editing instructions (Shu et al. 2024; Li et al. 2024). Other work (Chong et al. 2023; Li et al. 2025; Sarkar et al. 2025) incorporates implicit knowledge into prompts to steer generation toward personalization or task-specific objectives. However, these methods prioritize linguistic quality and personalization, they do not directly tackle visibility in GSEs. GEO (Aggarwal et al. 2024) is the first systematic effort targeting this problem, introducing GEO-bench, the first benchmark tailored for GSE scenarios, along with rule-based strategies that target semantic prominence. Despite its initial success, GEO is constrained by static rewrite patterns which lack adaptability to diverse query intents. Meanwhile, a line of work (Kumar and

Lakkaraju 2024; Pfrommer et al. 2024; Greshake et al. 2023; Shi et al. 2024; Bardas et al. 2025) explores prompt injection strategies to manipulate GSE responses, but these methods might compromise semantic coherence, raising concerns regarding safety and content integrity.

In contrast to static rewriting or prompt injection, we propose a multi-stage optimization framework based on explicit search intent modeling and role-augmented reflective prompting. Instead of injecting adversarial or misleading prompts, we decompose search intent into actionable sub-goals and align them with role-specific informational expectations. This enables targeted content enhancement that preserves semantic integrity while adaptively enhancing visibility under opaque and non-deterministic GSE behaviors.

Methodology

Blackbox GSE Assumption

In real-world deployments, GSEs such as Google’s Search Generative Experience (SGE) and Perplexity.ai typically adopt LLM-based RAG architectures while remaining largely opaque to external observers. To contextualize our work, we describe a typical GSE workflow, as illustrated in Figure 1. Upon receiving a user query q , the system retrieves a set of relevant content sources $C = \text{Retrieval}(q) = \{c_1, c_2, \dots, c_N\}$ from a corpus authored by diverse creators, including bloggers, journalists, encyclopedists, and government entities. The retrieved documents are then passed to an LLM to generate a natural language response $r = \text{generate}(C, q)$ composed of a sequence of sentences $\{l_s\}_{s=1}^m$. Each sentence l_s is linked to one or more evidence citations referencing sources $C_t \subseteq C, 1 \leq |C_t| \leq N$.

Our goal is to improve the visibility of a target content item $c_i \in C$ within the final response r through content-level optimization. We adopt the visibility evaluation settings and metrics proposed in GEO-bench and further extend them to broader scenarios. Crucially, we consider a black-box setting where the query q is hidden from content creators, posing a fundamental challenge for G-SEO. To address this, we propose the RAID-GEO method, an intent-driven framework that infers the likely user intent from the creator’s perspective and guides content rewriting accordingly, thus increasing the likelihood that the content will be selected or cited in GSE-generated outputs.

Intent-Driven Four-Phase Optimization

Given the early-stage nature of G-SEO and the absence of a well-established paradigm, we draw critical inspiration from traditional SEO strategies to address this gap. Although conventional approaches, such as those based on keyword tuning or webpage structure modifications (Kowalczyk and Szandala 2024; Samarah et al. 2024; Nagpal and Petersen 2021), are not directly applicable to the semantics-driven generation process inherent to GSE, their underlying principle remains valuable: anticipate search intent and tailor content expression accordingly. Building on this insight, we introduce search intent as a semantic intermediary that bridges latent user needs and optimized content. In our framework,

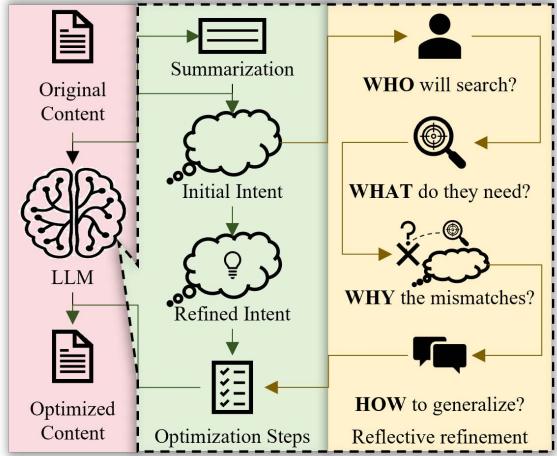


Figure 2: Overview of the Role-Augmented Intent-Driven G-SEO method. The method leverages search intent to guide the optimization process and further integrates reflection-based modeling from multiple roles to enhance generalizability to diverse user needs in complex GSE scenarios.

search intent is defined as the underlying informational motivation or objective implicitly embedded within a user’s query. It serves as the semantic anchor guiding the trajectory and strategy of content optimization. Recent advances in prompt engineering have enabled LLMs to make significant progress in intent understanding (Sun et al. 2024; Kim et al. 2024; Mao et al. 2023; Wang et al. 2021). To operationalize these advances in the context of G-SEO, we propose a novel framework: Role-Augmented Intent-Driven Generative Search Engine Optimization (RAID G-SEO) which implements a four-stage optimization pipeline driven by inferred search intent. The core stages are outlined below:

- Step 1: Content Summarization. We employ an LLM to conduct a semantically-focused summarization of the target content, using a constrained summarization prompt to suppress stylistic redundancy and semantic noise. This step enables the model to distill the content’s core informational focus as intended by the creator. As demonstrated in our ablation study, this summarization substantially improves the effectiveness of the downstream intent inference process.
- Step 2: Intent Inference and Refinement. We adopt a two-stage modeling approach to infer search intent. First, the LLM generates an initial intent representation based on the original content and its summary. However, this initial form often reflects the creator’s subjective projection of user interest, which may not generalize across user populations. To address this, we introduce a 4W multi-role deep reflection module, which enhances the initial intent via structured introspection from multiple user-role perspectives. Drawing inspiration from socio-logical decision frameworks, this module performs role-augmented, structured reasoning over four axes (Who, What, Why, How), guiding the model to reanalyze and

Method	Objective Impression(PAWC)			Subjective Impression								
	Word Count	Posi. Count	Over.	Rele.	Infl.	Uniq.	Dive.	Clic.	Sub.Posi.	Sub.Volu.	Aver.	
Tran. SEO	1.50	1.74	2.28	-0.47	-0.60	-1.11	0.59	0.73	0.30	1.22	0.11	
Uniq. Word	-0.53	1.26	1.40	-1.30	-2.49	-1.61	0.32	-1.65	-1.94	-1.48	-1.35	
Simp. Expr.	0.30	1.35	1.94	-0.55	-1.32	-1.39	0.38	1.00	-1.98	1.18	-0.43	
Auth. Expr.	-0.54	0.52	0.75	-0.05	-1.02	5.38	0.36	1.36	1.48	0.64	0.88	
Flue. Expr.	1.09	1.27	2.53	-0.22	-1.09	2.88	-0.15	0.78	0.14	-0.18	0.15	
Term. Addi.	5.96	7.12	8.07	2.11	<u>2.33</u>	10.25	1.96	<u>5.22</u>	2.74	3.62	3.63	
Repu. Addi.	0.13	1.09	1.85	-0.61	-0.80	0.31	0.69	-0.28	-0.10	1.44	0.05	
Quot. Addi.	3.76	5.40	5.33	1.87	0.91	4.38	1.63	1.22	0.84	3.65	1.97	
Stat. Addi.	4.35	6.37	7.03	1.81	1.58	9.63	1.61	4.93	1.97	3.58	3.27	
RAID G-SEO	7.81	8.14	8.49	2.24	2.29	15.93	2.01	4.77	6.16	5.09	4.72	

Table 1: Objective and subjective performances of G-SEO methods on the expanded GEO-bench. Results for the proposed RAID G-SEO are shown in bold, and the best-performing baseline for each metric is underlined. As both Objective impression Improvement and Subjective Impression Improvement consist of multiple sub-metrics, we report the overall score of the former and the average score of the latter as the main comparative indicators, following the original GEO-bench evaluation protocol to ensure fair and consistent comparison across methods.

refine the search intent toward broader user alignment. Details of this module are provided in the next section.

- Step 3: Step Planning. To minimize semantic drift during content rewriting, we prompt the model with the refined intent and instruct it to generate a sequence of explicit and interpretable optimization steps. This prompt-based planning decomposes the semantic intent into actionable revision strategies, enabling controllability and ensuring that subsequent edits preserve the intended semantic core.
- Step 4: Content Rewriting. Following the planned steps, the model conducts intent-aligned rewriting to improve both semantic alignment and retrieval effectiveness. By enforcing consistency with the inferred intent and adhering to the step plan, the rewritten content achieves higher relevance and compatibility with potential user queries, especially under black-box GSE settings where query visibility is unavailable.

Our RAID G-SEO framework is specifically designed to address the query-invisible nature of black-box GSE systems. By modeling latent user intent as a mediating signal and optimizing content from the creator’s perspective, our method provides a principled and structured optimization path. This approach effectively mitigates semantic misalignment between content expression and user retrieval motivations, thereby improving the adaptability and visibility of content across diverse GSE scenarios.

4W Multi-Role Deep Reflection

To address the heterogeneity of user groups in diverse retrieval scenarios, it is essential to enhance the generalizability of search intent representation, enabling it to cover a broader spectrum of potential information needs. In the black-box setting of G-SEO, where creators lack direct ac-

cess to user queries, we introduce a LLM-driven reflection mechanism to expand the semantic boundaries of the initially inferred intent. Reflection strategies have demonstrated efficacy in improving LLM performance across a variety of tasks (Shinn et al. 2023; Ji et al. 2023), especially in multi-perspective reflection paradigms (Zhang et al. 2024; Yan et al. 2024). These studies highlight LLMs’ capacity to simulate diverse cognitive roles and to construct alternative reasoning trajectories. However, most existing approaches rely on intuition-driven human-like reflection, lacking formal cognitive structure and scientific grounding. As such, they fall short in achieving the dual objective of semantic consistency and expressive breadth, both of which are essential for robust intent generalization in complex tasks.

To overcome these limitations, we draw inspiration from sociological theories of problem framing and decision-making (Ward 2017; Škérienė and Jucevičienė 2020). Specifically, we tailor this perspective to the G-SEO context by incorporating WH-analysis principles, which guide the model in decomposing and refining search intent from four critical dimensions: Who, What, Why, and How. In particular, the Who offers a multi-perspective lens, while intermediate outputs of the What and Why serve as constraints and guidance signals in the semantic reconstruction process of the How. This promotes intent representations that are both aligned and diversified. This forms the foundation of our multi-role reflective framework, enabling LLMs to reinterpret the initial intent through augmented user-role reasoning. The 4W framework operates as follows:

- Who is likely to retrieve this content? To balance generalization and precision, we prompt the LLM to infer a set of representative user roles most likely to search for the content (e.g., technical professionals, general readers, or decision-makers), based on the initial intent.

- What are their retrieval needs? For each inferred user role, the model conditions intent generation on their domain background and knowledge profile, producing candidate motivations and search goals. By embedding role-specific constraints, uncontrolled semantic drift is limited to ensure higher factual alignment between generated intent and plausible needs.
- Why does the initial intent misalign with their needs? The model is tasked with identifying semantic gaps between the original intent and each role-specific need, followed by an explanation of the misalignment causes. This step enables targeted and directed generalization, rather than generic expansion.
- How should the initial intent be generalized? Leveraging the structured reflection outputs from the prior steps, we instruct the model via prompt-based reasoning to semantically reconstruct the initial intent. The refined version preserves the core informational focus while expanding its scope and adaptability across user contexts.

Importantly, the entire reflection process is fully automated via prompt-based reasoning, requiring no human annotation or intervention, which ensures scalability across GSE settings. Through the 4W multi-role deep reflection module, we derive intent representations that maintain semantic coherence while effectively generalizing to diverse retrieval scenarios. The enhanced intent serves as a robust foundation for downstream G-SEO optimization, allowing the final content to achieve higher alignment with latent user queries.

All prompts employed in the Methodology Section are structurally designed and documented in Appendix A.

Experiments

Experimental Setup

To ensure reproducibility and fairness, full generation configurations (e.g., sampling strategy, temperature, top-p) are included in Appendix D.

GSE Simulation Following GEO (Aggarwal et al. 2024), we simulate the GSE task as a single-turn response generation scenario, where each query has access to five content sources. We use the open-source GLM-4-9B-0414 model, which exhibits a low hallucination rate according to the Hallucination Leaderboard (Hughes, Bae, and Li 2023). To ensure consistency and minimize statistical bias, we adopt the same prompting and sampling configurations used for answer generation as in prior work.

Dataset To better model diverse retrieval scenarios, we extend GEO-bench (Aggarwal et al. 2024), a benchmark comprising real-world queries from production systems (e.g., Bing, Google, Perplexity), complex reasoning tasks, and LLM-generated questions. To enhance query diversity, we use GPT-4 to generate four semantically related variants for each original query, forming evaluation samples with five related queries and their corresponding five content sources. We randomly select 100 such samples for evaluation (seed = 42).

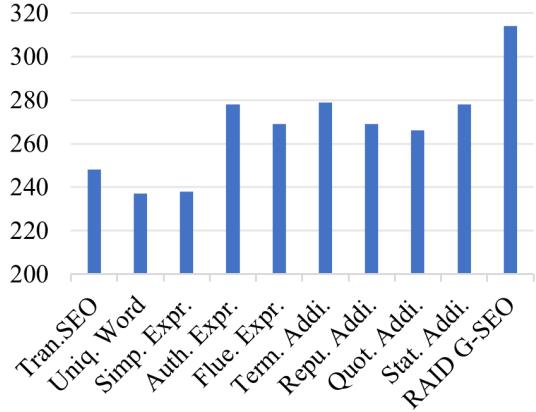


Figure 3: Adaptability of G-SEO methods across diverse GSE retrieval scenarios. We evaluate each method’s adaptability by counting the number of optimized content instances that yield observable improvements in subjective visibility across multiple retrieval tasks. This reflects the generalization capacity and real-world utility of each approach.

Baselines We adopt all nine optimization methods from GEO (Aggarwal et al. 2024) as comparison baselines, grouped into three categories:

- Lexical strategies: Traditional SEO and distinctive word optimization, which enhance visibility through keyword insertion and rare lexical choices.
- Expression enhancements: Authority-, fluency-, and simplification-based methods that improve content credibility, clarity, and readability.
- Content enrichment: Terminology-, reputation-, quotation-, and statistics-based methods that incorporate factual or semi-factual elements (e.g., domain-specific terms, reputable sources, quotations, and quantitative evidence) while remaining contextually plausible.

All baselines and our proposed intent-driven method are implemented using GLM-4-9B and evaluated under identical conditions.

Evaluation Metrics We evaluate G-SEO methods using both objective and subjective metrics defined in GEO-bench (Aggarwal et al. 2024), focusing on impression-based improvements before and after optimization. For objective evaluation, we adopt Position-Adjusted Word Count (PAWC), which assigns greater weight to cited content appearing earlier and more frequently. Subjective evaluation follows the Subjective Impression metric, encompassing seven subjective dimensions: relevance, fluency, diversity, uniqueness, click likelihood, subjective positional prominence, and subjective content volume. GEO originally employed G-Eval (Liu et al. 2023) to simulate human judgment, but its prompts lacked consistent granularity and clear criteria. To improve scoring reliability, we adopt a prompt-generate-prompt strategy: each dimension is rated on a 0

Method	Subjective Impression (Aver.)
Simple G-SEO (w/o Step)	1.54
Simple G-SEO (/w Step)	3.76
ID G-SEO (w/o summ.)	-3.18
ID G-SEO (w/ summ.)	2.96
RAID G-SEO	4.72

Table 2: Ablation settings and results of RAID G-SEO. To evaluate the structural role of search intent modeling in the RAID G-SEO framework, we design two ablation variants: (1) Simple G-SEO, which removes the intent reasoning phase and performs optimization directly based on the original content; (2) ID G-SEO, which retains the initial intent modeling phase but removes the 4W multi-role deep reflection module, relying only on initial intent. RAID G-SEO and both ablated variants are evaluated under identical settings and task conditions.

(absent) to 5 (optimal) scale, with prompts generated by GPT-4o and responses evaluated using GLM-4-9B. We provide the prompt-generation prompt and a unified template in Appendix C. To quantify relative improvement, we normalize visibility scores. For each citation C_i , the improvement from the original response r to the optimized response r' is computed as:

$$improvement_{C_i} = \frac{impr_{C_i}(r') - impr_{C_i}(r)}{impr_{C_i}(r)} \times 100$$

Additional evaluation details are available in Appendix D.

Results and Analysis

Main Result We conducted a comprehensive evaluation of RAID G-SEO against nine representative optimization baselines from GEO (Aggarwal et al. 2024), as summarized in Table 1. RAID G-SEO achieved the highest performance across both primary evaluation dimensions, with an improvement of +0.42 in Objective Impression (Overall) and +1.09 in Subjective Impression (Average), significantly surpassing the second-best method (terminology-based). Although RAID G-SEO showed slightly lower scores on some subjective sub-dimensions (e.g., influence and click-follow likelihood), it consistently led in aggregate subjective metrics, demonstrating its strong ability to enhance overall perceived quality. These results highlight a notable shift in optimization strategies between traditional SEO and G-SEO tasks from the perspective of user perception: rather than optimizing local indicators (e.g., keyword density or citation authority), GSE frameworks tend to prioritize global impression quality as perceived by LLM. Notably, the traditional SEO baseline performed poorly under this evaluation with only +2.28 in objective and +0.11 in subjective gains, ranking sixth on average, highlighting limited adaptability in GSE contexts. Furthermore, terminology-based and statistics-based methods achieved second and third respectively, significantly outperforming authority- and reputation-based strategies. This trend indicates a latent preference of



Figure 4: Distribution of RAID G-SEO across multi-role perspectives. We perform semantic clustering on the user role descriptions generated by the 4W multi-role deep reflection module to characterize the types of cognitive perspectives involved during intent generalization. The results illustrate the relative frequency of each role category, reflecting the model’s response pattern to perspective distribution during optimization.

LLMs for content with strong perceived expertise over externally validated authority. We hypothesize that this behavior may arise from distributional priors in pretraining corpora, offering insights for future research on model alignment and retrieval-centric knowledge calibration.

Adaptability Analysis To evaluate the adaptability of different methods in diverse GSE scenarios, we adopt Subjective Impression Improvement (Average) as the core evaluation metric. A total of 500 retrieval tasks are sampled to assess each method’s effectiveness in integrating multi-source information and generating coherent answers, as illustrated in Figure 4. The results show that RAID G-SEO achieves an effective optimization rate of 62.8%, outperforming the second-best terminology-based optimization method (55.8%) by 7.0 percentage points, demonstrating stronger generalization ability and robustness in diverse retrieval settings. Notably, none of the evaluated methods exceed the 70% effectiveness threshold, underscoring the challenges of achieving stable content optimization in the GSE environment. This suggests that robust adaptation in such scenarios remains an open and valuable research direction.

Ablation Study We conduct an ablation study by progressively incorporating different prompt-based reasoning modules into the RAID G-SEO framework. Subjective Impression Improvement (Average) is adopted as the primary evaluation metric to assess the contribution of each component to the content optimization task. As shown in Table 2, the overall optimization performance of RAID G-SEO consistently improves with the addition of reason-

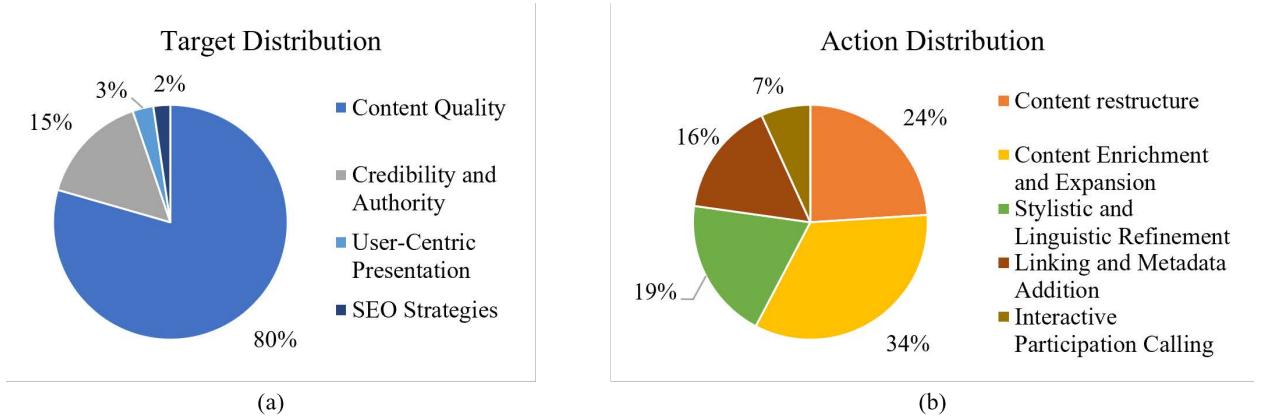


Figure 5: Distribution of optimization step preferences in RAID G-SEO. Each generated optimization step is structurally parsed to identify its corresponding optimization objective and operational strategy type, followed by semantic clustering. Subfigure (a) shows the distribution across intent-aligned target dimensions (e.g., enhancing content completeness, improving factual credibility, increasing clarity), indicating where the intent prioritizes refinement. Subfigure (b) presents the distribution over strategy categories (e.g., content restructuring, elaboration, redundancy reduction), capturing the model’s typical operational behavior under intent-driven guidance.

ing stages, demonstrating the effectiveness of our proposed intent-driven four-phase optimization framework and the accompanying 4W multi-role deep reflection module. Notably, ID G-SEO (without summarization) is the only variant that yields a negative score. We hypothesize that inferring the initial intent directly from raw, unsummarized content introduces noise and redundancy, thereby degrading the performance of the downstream optimization module. In contrast, Simple G-SEO (with step planning), despite lacking explicit user intent modeling, outperforms both ID G-SEO variants. This suggests that the optimization step planning module may implicitly capture latent user needs and align more effectively with user search intents. These findings provide meaningful guidance for enhancing the precision and robustness of intent modeling in future work.

Preference Analysis Role Perspective Preference Distribution. In the 4W multi-role deep reflection module of RAID G-SEO, we generate diverse user role perspectives based on the content creator’s preliminary assumptions about user search intents, leveraging prompt-based LLM. A total of 8,030 role instances spanning 219 distinct role types were collected and subjected to semantic clustering, with the distribution visualized in Figure 4. The analysis reveals that RAID G-SEO predominantly favors two cognitive perspectives: Knowledge Producers and Researchers (e.g., Educator, Policy Maker) and Civic Everyday Actors (e.g., Home Cook, DIY Hobbyist), which together account for over two-thirds of the role instances. In contrast, Health and Care Stakeholders and Cultural and Creative Professionals represent only 6% and 3% of the total, respectively, often corresponding to more specialized or context-dependent viewpoints, while Economic Activity Participants fall in the mid-range. This distribution suggests a tendency of the model to prioritize generalizable, publicly oriented perspectives during intent generalization. These findings provide empirical support for the role modeling mechanism in facilitating broader intent coverage. Optimization Steps Preference Distribution. To analyze how search intent informs downstream optimization behaviors, we perform structured semantic parsing of all optimization steps generated during the Step Planning phase of RAID G-SEO. Each step is annotated with its corresponding optimization objective and operation type, followed by semantic clustering, as illustrated in Figure 5. The results indicate that over 80% of the optimization steps explicitly target content quality enhancement, covering objectives such as improving completeness and clarity. In terms of operational strategies, Content Enrichment and Expansion accounts for more than 30% of all actions, suggesting that the model, when guided by intent, tends to prioritize enriching informational content as a primary optimization strategy. Overall, RAID G-SEO exhibits a multi-dimensional hybrid planning approach that better accommodates the complexity of GSE tasks, where the empirical improvements observed further validate the effectiveness of intent-guided optimization.

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Conclusion

This work addresses the task of generative search engine optimization under diverse retrieval scenarios, and introduces an intent-generalization-enhanced optimization approach. We design an intent-driven four-phase optimization framework, and incorporate a 4W multi-role deep reflection mechanism to improve the generalizability of the inferred intent, enabling creators to perform adaptive and targeted content optimization even in the absence of explicit user queries. To support more comprehensive and objective evaluation, we extend GEO-bench to cover a broader range of retrieval scenarios, and develop G-eval 2.0, a fine-grained subjective evaluation framework for assessing content visibility. Experimental results demonstrate that intent modeling

plays a pivotal role in G-SEO, with generalized intent representations contributing significantly to optimization effectiveness. Nevertheless, balancing the precision and generalizability of intent representations remains a key open challenge.

Limitations While our results demonstrate that incorporating search intent provides more focused guidance for optimization in G-SEO tasks, we observe that overly specific intents may lead to content rewrites that overfit to particular queries, thereby reducing generalizability. This observation underscores a central challenge in targeted G-SEO: balancing the precision of intent modeling with the adaptability of optimization strategies. Our approach relies primarily on prompt engineering for preliminary intent extraction, which remains limited in granularity control and contextual consistency. Future work may explore integrating domain-specific knowledge or developing dedicated intent modeling modules to improve the effectiveness of G-SEO methods. Furthermore, our proposed method, like most existing G-SEO approaches, focuses solely on plain text without accounting for visual or multimodal elements such as images, diagrams, or tables that may influence content visibility in real-world GSEs. Extending G-SEO to Visual-Language Models (VLMs) for unified multimodal optimization poses an important avenue for future research.

Ethical Statement We strictly adhere to the ethical standards and best practices of the AI research community. We employ LLMs in full compliance with their licensing terms. Our study focuses on improving content visibility within GSEs. All experiments are conducted in simulated environments without interfering with, misleading, or manipulating the behavior of any real-world systems. To support evaluation, we extend the GEO benchmark by generating synthetic text data using the LLM and applying targeted optimizations. All generated or modified content is intended solely for research and experimentation. The resulting data does not reflect factual information and should not be interpreted as expressing any subjective opinions or value judgments of the authors or the underlying models.

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