LongScope 🔭: Entropy-Driven Convolutional Test-Time Scaling for Generating Long-Form Articles from Extremely Long Resources

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Abstract

Long-form generation is crucial for a wide range of practical applications, typically categorized into short-to-long and long-to-long generation. While short-to-long generations have received considerable attention, generating long texts from extremely long resources remains relatively underexplored. The primary challenge in long-to-long generation lies in effectively integrating and analyzing relevant information from extensive inputs, which remains difficult for current large language models (LLMs). In this paper, we propose LongScope, a novel test-time scaling strategy designed to enhance the ability of LLMs to process extremely long inputs. Drawing inspiration from convolutional neural networks, which iteratively integrate local features into higher-level global representations, LongScope utilizes stacked convolutional scaling layers to progressively expand the understanding of input materials. Both quantitative and qualitative experimental results demonstrate that our approach substantially enhances the ability of LLMs to process long inputs and generate coherent, informative long-form articles, outperforming several representative baselines.

1 Introduction

Long-form text generation using large language models (LLMs) holds significant application value and is gaining growing attention (Wang et al., 2024b; Shao et al., 2024; Xi et al., 2025). Based on the amount of information the model should process, long-form text generation can be broadly categorized into two types: **short-to-long** generation and **long-to-long** generation. In short-to-long generation, the model produces long texts from a concise prompt (Fan et al., 2019; Krishna et al., 2021). In contrast, long-to-long generation entails the model producing detailed articles that rely not only on writing prompts but also on a broad range of input data.

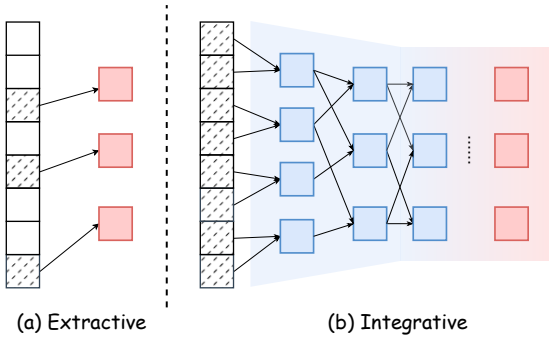


Figure 1: Comparison between traditional extractive methods and integrative approach for resource utilization in long-form generation. Extractive methods select relevant content based on queries, which may overlook important information not directly aligned with the query. In contrast, the integrative approach synthesizes a broader range of content, capturing connections for a more comprehensive understanding.

There are two major challenges for long-to-long generation: (1) **resource collection**: retrieving relevant materials for the given topic; and (2) **resource utilization**: effectively integrating these materials to produce informative and cohesive results. Several recent studies focus on improving the resource collection process. For example, STORM (Shao et al., 2024) uses a multi-agent system to pose questions from various perspectives, thereby expanding the coverage of retrieved documents. OmniThink (Xi et al., 2025) further develops a growing information tree to progressively expand and deepen the knowledge scope of the collected resources. In real-world scenarios, the relevant resources can be vast (Wang et al., 2024b), making it challenging for modern LLMs or even human experts to extract and synthesize key insights from large volumes of information while analyzing and identifying significant patterns.

Therefore, we focus on enhancing the **resource utilization** capabilities of LLM-based **long-to-long**

generation frameworks. To address the issue that the collected resources exceed the effective context length of LLMs, most existing methods employ extractive techniques to compress the resources (Wang et al., 2024b; Xi et al., 2025). A common approach is to use embedding models to identify the most relevant chunks based on the queries. A major limitation of extractive methods is that they may overlook important content that, while relevant, does not directly align with the given queries. This can include critical analyses, nuanced insights, or broader contextual information that might not be immediately similar but could provoke deeper reflection or contribute to a more comprehensive understanding of the topic.

In this work, we shift from traditional **extractive** methods to **integrative** approaches, aiming to synthesize a broader range of information and draw connections between different pieces of content to create a more holistic and nuanced representation. Specifically, we begin with a theoretical analysis of the long-to-long generation task from the information bottleneck perspective. This analysis underscores the importance of intermediate textual representations, for which we introduce a skeleton and a series of resource digests. By enhancing the informativeness of these intermediate elements, we can theoretically improve the lower bound on the amount of information in the final output. To facilitate effective information aggregation, we propose a novel randomized convolutional test-time scaling method. Our approach draws inspiration from the classic convolutional neural network (LeCun et al., 1998), which progressively abstracts local features into high-level global representations, a technique widely used in image processing. We also introduce an information entropy estimation module to guide the convolution process, helping the test-time scaling procedure consistently enhance the informativeness of the results. The resulting long-to-long generation framework, which we term *LongScope*, effectively helps existing LLMs process extremely long sequences.

Moreover, to evaluate the performance of the proposed integrative framework in comparison to previous extractive methods, we develop a high-quality survey writing benchmark, *SurveyEval*. This benchmark consists of academic surveys covering diverse topics, along with their corresponding reference papers. To the best of our knowledge, SurveyEval is the first scalable evaluation benchmark that includes surveys paired with complete reference papers. We selected the survey writing task because it is a quintessential example of generating articles from extensive resources. This task requires the model to thoroughly comprehend the provided reference papers and synthesize informative results that reflect both the current state and future trends of a specific topic. Experimental results on SurveyEval demonstrate that our proposed method consistently outperforms several representative baselines, showcasing the effectiveness of the proposed integrative method.[1]

Our main contributions include:

- We conduct a theoretical analysis of the **long-to-long** generation task, identifying that the key challenge lies in constructing and leveraging informative intermediate representations.
- We create a high-quality **long-to-long** generation benchmark **SurveyEval**, the first evaluation benchmark in the domain of computer science that pairs surveys with complete reference papers, enabling a thorough comparison of **resource utilization** capabilities.
- We propose an entropy-driven convolutional test-time scaling framework **LongScope** to use **integrative** method to solve the **resource utilization** problem in the **long-to-long** scenario, with at least 32.9% improvement in the reference utilization rate and better than the extractive baseline in other dimensions.

2 Information Bottleneck Analysis

Long-to-long generation necessitates information compression to conform to the resources within the context window of LLMs and depends on the intermediate representation for constructing the final output, which aligns with the Information Bottleneck (IB) (Tishby and Zaslavsky, 2015) theory. It has the following basic forms:

$$IB(X, Y) = I(Z; Y) - \beta I(X; Z), \quad (1)$$

where X is the input source, Z is the intermediate representation and Y is the output. $I(\cdot, \cdot)$ represents the mutual information between them. β denotes a positive Lagrange multiplier.

Let X be the input materials, which include the topic T of the required output article (i.e., Y)

[1]This work relies entirely on open-source tools and publicly available data. All code and data will be open-sourced once the paper is de-anonymized.

and the provided resources R, which may be very lengthy. For intermediate representations, we introduce the skeleton S, aligned with the output Y, and the digests D, which are compressed summaries derived from the resources R. The information bottleneck can be given by

$$IB(X,Y) = I(Y;D) - \beta H(D), \tag{2}$$

where $H(\cdot)$ represent the information entropy. The detailed derivation from Eq. (1) to Eq. (2) can be found in Appendix A.

Subsequently, given the information inclusion relationship between the variables, we can get the upper and lower bounds of IB:

$$\begin{aligned} IB(X,Y) \geq & \min((1-\beta)H(D) - H(D|Y), \\ & H(S) - \beta H(D)), \\ IB(X,Y) \leq & H(Y|D) + (1-\beta)H(D). \end{aligned} \tag{3}$$

The detailed derivation process can also be found in Appendix A. The bounds shown in Eq. (3) imply four optimization objectives for the long-to-long generation task:

- Maximizing $(1-\beta)H(D)$, which means improving the information in the digests.
- Maximizing $H(S)$, which means enhancing the information in the skeleton.
- Minimizing $H(D|Y)$, which means reducing the information in the digests that are not used in the final output.
- Maximizing $H(Y|D)$, which means incorporating additional information beyond the digest when writing the Survey.

In this work, we focus on optimizing the first three objectives to improve the lower bound of the information bottleneck. Optimization of the last objective is left for future work.

3 LongScope

Guided by the IB principle, our method employs skeleton-guided digest generation to more effectively extract information from full papers (Sec. 3.1), entropy-driven convolution and a best-of-N self-refinement mechanism to enhance skeleton quality (Sec. 3.2), and topology-aware content generation to leverage the information in the digests (Sec. 3.3).

3.1 Initialization

Survey Tree Construction Throughout the process, both the skeleton and paper digests are parsed into a tree structure that mirrors the generated markdown document. We denote this tree as $\mathcal{T} = (V, E)$, where V is the set of nodes corresponding to section headings, and E defines the parent-child relationships between these nodes. Each skeleton node consists of two key components: Digest Construction, which outlines how to build paper digest nodes, and Digest Analysis, which specifies how these digest nodes will be utilized during the writing process. Figure 2 illustrates an example of the skeleton structure.

```
### 2.1 Section Title
Digest Construction:
Write about what information
should be extracted from the full
paper in this section.
Digest Analysis:
Write about how to organize
and analyse papers ["BIBKEY1",
"BIBKEY2"] with executable step.
```

Figure 2: Example of the structure in the skeleton.

Skeleton Initialization Before generating the digest, an initial skeleton framework should be established based on the given topic T and a collection of reference resources $R = \{r_1, r_2, \ldots, r_K\}$. To balance efficiency and performance, the references are first grouped into clusters, denoted by $\mathcal{C}(R) = \{C_1, C_2, \ldots, C_J\}$, such that $\bigcup_{j=1}^{J} C_j = R$. For each cluster C_j, a local skeleton is generated using an LLM-based initialization function $\mathcal{I}(\cdot)$, and then aggregated using the LLM-based function f_{agg} to form a unified initial skeleton:

$$S^{(0)} = f_{\text{agg}}(\sum_{j=1}^{J} S_j) = f_{\text{agg}}(\sum_{j=1}^{J} \mathcal{I}(T, C_j)).$$

Skeleton-Guided Digest Generation To more accurately and comprehensively compress the content of each reference, the skeleton is used to guide the digest generation. As shown in Figure 2, the skeleton includes a Digest Construction component that directs the creation of the digests. Based on the general guidelines provided by the skeleton and the specific content of each reference article r, the LLM generates a concise digest D_r tailored to the current skeleton. Furthermore, to foster collaborative optimization between the skeleton and the

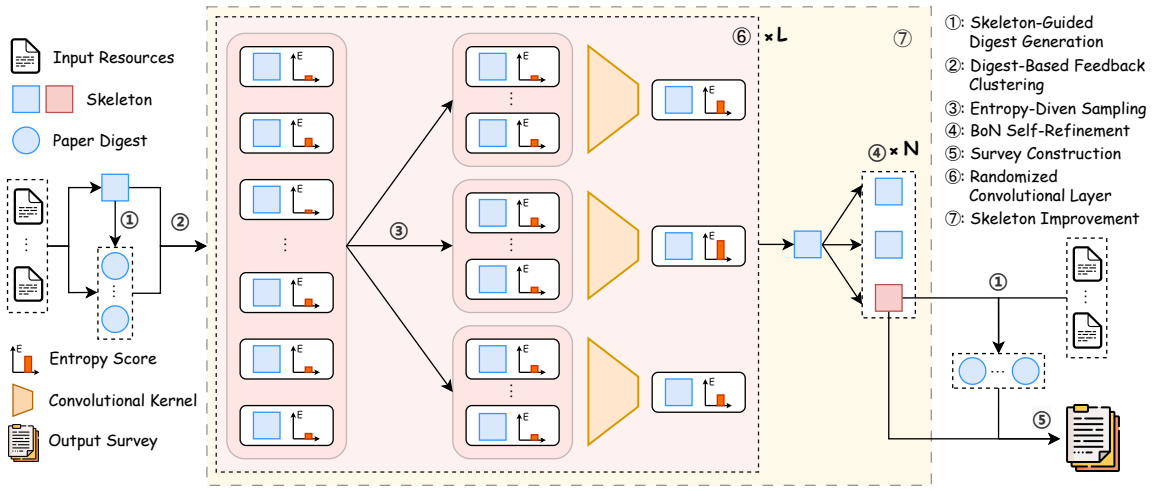


Figure 3: The pipeline of LongScope. LongScope can be roughly divided into three stages. In the Initialization phase, LongScope initializes the skeleton based on the vast resources and the given topic, and generates the corresponding structured digests. In the Skeleton Improvement phase, LongScope utilizes the feedback from the digests to refine the skeleton, which is guided by entropy-driven random sampling and multi-layer convolution for feedback aggregation. Additionally, a series of Best-of-N iterations are employed to further enhance the skeleton. In the Survey Construction phase, LongScope regenerates structured digests based on the optimized skeleton and performs topology-aware content generation to produce the final survey.

digests, we require the LLM to propose associated feedback F_r for the skeleton, which provides informative suggestions for the subsequent skeleton improvement process.

3.2 Skeleton Improvement

The skeleton plays a pivotal role in bridging the input and output. Its Digest Construction component guides the extraction of information from references into the digest, while the Digest Analysis part provides instructions for organizing the digests into the final survey content. To fully leverage the potential of test-time scaling and obtain better skeletons, we design two mechanisms: Entropy-Driven Convolution and Best-of-N Self-Refinement.

Inspired by residual (He et al., 2015), where $H(x) = x + f(x)$, we develop feedback ΔS to modify the skeleton, rather than directly generating a new one. This approach better captures the differences between intermediate skeletons, reducing information redundancy for LLMs during the process. Each feedback ΔS first modifies the base skeleton to produce the updated version $S + \Delta S$, after which the information entropy is evaluated. This entropy is then used to guide the improvement of the skeleton.

To better quantify the information entropy within the skeleton, we split it into two parts: the title structural information entropy $H_T(S)$ and the chapter description information entropy $H_C(S)$. Their combined effect is modelled as

$$H(S) = H_T(S) + H_C(S).$$

We use LLM-as-judge (Gu et al., 2025) to get a score out of ten as an estimation of information entropy.

3.2.1 Entropy-Driven Convolution

Digest-Based Feedback Clustering Based on the initialized skeleton $S^{(0)}$, we have generated new digests D_r and feedback F_r. During this process, we need to aggregate the information within each cluster C_j to generate the initial skeleton modification suggestions at the cluster level. Specifically, for cluster C_j, we use an LLM-based function f_{part} to aggregate the information within it and generate partial feedback:

$$\Delta S_j^{(0)} = f_{\text{part}}(\bigoplus_{r \in C_j} D_r, \bigoplus_{r \in C_j} F_r),$$

where $1 \le j \le J$, and $\Delta S_j^{(0)}$ represents the modification feedback based on the information within C_j. All initial partial feedback will enter multiple randomized convolutional layers for further aggregation.

Entropy-Driven Sampling and Convolution Inspired by the hierarchical feature aggregation in

convolutional neural networks, we perform multi-layer convolution on the aggregated partial skeleton feedback. Because of the absence of natural spatial adjacencies, we incorporate an entropy-driven randomized sampling process. At the l-th layer, each feedback item ΔS_i^l is sampled with a probability defined by:

$$p^{(l)}(\Delta S_i^{(l)}) = \frac{H(S + \Delta S_i^{(l)})}{\sum_{i=0}^{N} H(S + \Delta S_i^{(l)})},$$

where N is the number of feedback in this layer. From this distribution, multiple sets of feedback items are selected:

$$\Delta \hat{S}_j^{(l)} = \text{Sample}\Big(\{\Delta S_i^{(l)}\},\, p^{(l)},\, k\Big).$$

The number of sets is determined by hyperparameters `result num`, i.e., $1 \le j \le$ `result num`. These sampled feedback sets are then integrated parallelly using f_{conv} as a convolution function:

$$\Delta S_j^{(l+1)} = f_{\text{conv}}\Big(\Delta \hat{S}_j^{(l)}\Big),$$

where $1 \le i \le L$. And we select `top-k` feedback into the next layer. After L layers, the refined skeleton is obtained by selecting the best one of the last layer:

$$S_{\text{refine}} = S + \arg\max_{\Delta S_j^L} H(S + \Delta S_j^L).$$

3.2.2 Best-of-N Self-Refinement

After modifying by digest-based feedback, we use the Best-of-N strategy to make overall adjustments and organization. Specifically, `best-of` candidate feedbacks are independently generated from the S_{refine}, and the one with the highest entropy is selected:

$$S^{c+1} = S^c + \arg\max_{\Delta S_i^c} H(S^c + \Delta S_i^c),$$

where $1 \le i \le$ `best-of`. This will repeat `self-refinement step` times, i.e., $1 \le c \le$ `self-refinement step`. This selection ensures that the final skeleton S^* exhibits superior global information integration beyond references.

3.3 Topology-Aware Content Generation

In the final stage, the optimized skeleton S^* and the corresponding digests $\{D_r^*\}$ are used to generate the final survey. Because both the skeleton and the digests adhere to the tree structure $\mathcal{T} = (V, E)$, each node $v \in V$ corresponds to a section of the survey. We generate each section's content in node-level to reduce the number of details for fully utilizing the information in digests.

The content for each leaf section is generated using a function $g_{\text{leaf}}(\cdot)$, which is more focused on the utilization of details and comparison between specific works in multiple digests:

$$y_v = g_{\text{leaf}}\Big(s_v^*, \{d_{r,v}^*\}_{r \in R}\Big),$$

where s_v^* represents the refined skeleton Digest Analysis part for node v and $d_{r,v}^*$ is the digest information from reference r for that section.

As for the non-leaf section, to make the parent chapter more overarching and comprehensive, sub-section contents are additionally introduced in $g_{\text{non-leaf}}(\cdot)$:

$$y_v = g_{\text{non-leaf}}\Big(s_v^*, \{d_{r,v}^*\}_{r \in R}, \{y_{v'}\}_{e_{v \to v'} \in E}\Big).$$

4 Experiment

4.1 Dataset

We have developed a high-quality survey writing benchmark, **SurveyEval**, to support our experimental framework. To the best of our knowledge, SurveyEval is the first evaluation benchmark in the domain of computer science that pairs surveys with complete reference papers. In total, we collected 384 survey papers from the Internet, which together cite over 26,000 references.

Given that running, evaluating, and manually assessing the algorithms is time-consuming and labour-intensive, and to align with the AutoSurvey topic number (i.e., 20 surveys), we selected 20 articles from this collection as the test set. Detailed information on dataset construction and metadata is provided in Appendix B.

4.2 Baselines

We evaluate LongScope against three baselines, all powered by Gemini-2.0-flash-thinking-exp-1219 (Team, 2024a). The input to each baseline consists of the title and full reference papers from the test set. The baselines include

- *Vanilla*: Directly feeding the topic and full text of all referenced articles into the model for inference via standard decoding.
- *Vanilla+Skeleton*: Explicitly generating a skeleton before writing the full output, inspired by the AgentWrite framework (Bai et al., 2025).

- *AutoSurvey* (Wang et al., 2024b): A RAG-based academic survey generation framework. We applied the settings and parameters reported in their original work.

The implementation details can be found in Appendix C.

4.3 Evaluation Metrics

4.3.1 Automatic Metrics

The metrics are grouped into four main dimensions, with scores ranging from 0 to 100.

Structure-Oriented Metric This metric is used to evaluate the logical organization and coherence of each section, strictly adhering to the structural criteria of AutoSurvey. Details can be found in Appendix D.1.1.

Content-Oriented Metrics The evaluation metrics for assessing content quality are briefly introduced below. For a detailed explanation, please refer to Appendix D.1.2.

- *Faithfulness*: The precision of sentences with citations in the final output, where correctness is measured by whether the sentence is accurately supported by the cited resources (i.e., the reference papers in the survey writing task).

- *Relevance*: The degree to which the content aligns with the research topic, assessing how well the content stays focused on the required research question.

- *Language*: The assessment of academic formality, clarity, and the avoidance of redundancy in the survey. This metric evaluates the overall quality of writing, ensuring the language is clear, concise, and appropriate for an academic audience.

- *Criticalness*: The extent to which the survey demonstrates critical analysis, provides original insights and identifies future research directions. This metric evaluates how well the survey goes beyond summarizing existing work, offering thoughtful critiques and highlighting gaps, challenges, or opportunities for further investigation.

Claim-Oriented Metrics To assess the information amount and density of the survey, we drew inspiration from FactScore (Min et al., 2023) to extract claims from the surveys, ensuring that duplicates were removed. Based on this approach, we designed the following two metrics to evaluate both the richness and compactness of the information presented. The full extraction and deduplication procedures are detailed in Appendix D.1.3.

- *Number of Claims*: The total count of unique and accurate claims identified within the text. This metric evaluates the breadth of information presented in the survey by counting the number of distinct, informative claims made.

- *Density of Claims*: The ratio of unique claims to the total number of extracted claims before deduplication. This metric reflects the concentration of distinct, relevant information within the survey, indicating how efficiently the content conveys valuable insights. A higher density suggests a more focused and information-rich survey, whereas a lower density may imply redundancy or irrelevant content.

Reference-Oriented Metrics To assess the effective utilization of the provided references in the generated survey, we propose two metrics that measure the coverage and inclusion of references. These metrics aim to quantify the extent to which the input references contribute to the final content, ensuring both precision and comprehensiveness in reference usage. Specifically, we define the following metrics. Detailed can be found in Appendix D.1.4

- *Precision*: This metric quantifies the proportion of the input references that are correctly cited at least once in the survey. Precision evaluates how well the references are incorporated into the survey, ensuring that each reference is appropriately acknowledged in the text. A higher precision score indicates that most or all of the provided references have been correctly used in the survey, reflecting thorough integration of the source material.

- *Recall*: Recall measures the total number of input references that appear at least once in the generated survey. This metric captures the breadth of reference inclusion, providing an indication of how many of the input references were utilized overall. A higher recall suggests a more comprehensive survey, where a larger

Methods	Struct.	Content				Claim		Reference	
		Fait.	Rele.	Lang.	Crit.	Num.	Dens.	Prec.	Recall
Standard Decoding									
Vanilla	94.44	96.43	**100.00**	**96.50**	37.11	78.75	**74.64**	25.48	26.46
+ Skeleton	**98.95**	**97.03**	**100.00**	95.95	**41.01**	**135.15**	72.96	**62.60**	**65.11**
Test-Time Scaling									
AutoSurvey	86.00	93.10	**100.00**	92.90	68.39	423.35	31.97	50.12	51.73
LongScope	**95.00**	**97.22**	**100.00**	**94.34**	**71.99**	**474.90**	**52.23**	**95.50**	**95.80**

Table 1: Performance of the methods evaluated on SurveyEval. For details on the evaluation dimensions, please refer to Section 4.3. The highest scores within each category are bolded.

proportion of the input references are cited, while a lower recall may indicate that some references were overlooked or underutilized.

These two metrics together provide a balanced assessment of reference use in the survey, with precision focusing on the correct application of references and recall emphasizing their overall inclusion. Both are crucial for ensuring that the survey is grounded in relevant prior work while also reflecting an efficient use of the provided references.

4.3.2 Human Evaluation

To enable a more reliable comparison of the overall quality between LongScope and other baselines, we conduct a human evaluation. In this process, assessors are asked to determine which survey performs better on the same topic. The *win rate* is then computed based on these comparisons. Figure 4 shows the evaluation results. Further details of the evaluation procedure can be found in Appendix D.2.

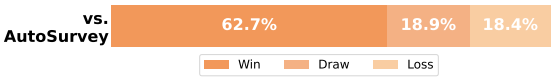


Figure 4: Human-evaluated win rate of LongScope compared to AutoSurvey on the test set.

4.4 Main Results

Table 1 presents the results of four involved methods across four dimensions. The results highlight that LongScope consistently outperforms the baseline methods in most dimensions.

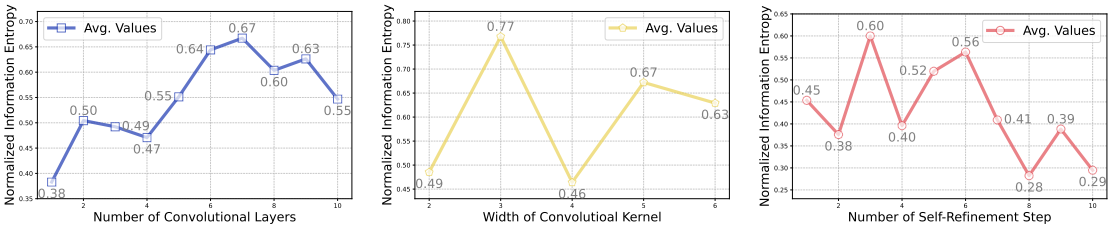
In terms of structural metrics, LongScope achieves a score of 95.00, which is higher than AutoSurvey (i.e., 86.00). The content-oriented metrics, which are crucial for understanding the effectiveness of the methods in generating meaningful and relevant output, show a significant advantage for LongScope. In terms of the faithfulness, LongScope scores 97.22, outperforming AutoSurvey (i.e., 93.10). LongScope also performs very well in critical thinking, with a score of 71.99, better than that of AutoSurvey (i.e., 68.39) and those of the standard decoding baselines.

When evaluating the claims, LongScope generates the largest number of informative claims, highlighting the effectiveness of the proposed entropy-driven convolutional test-time scaling mechanism. Additionally, LongScope exhibits a significantly higher density than AutoSurvey, underscoring the superiority of the integrative approach over the extractive method. Although standard decoding strategies can achieve a high claim density, the total number of unique claims is significantly lower than that of test-time scaling approaches.

Finally, LongScope outperforms the baselines in the reference metrics as well, achieving the highest precision (i.e., 95.50) and recall (i.e., 95.80), significantly surpassing both standard decoding baselines and AutoSurvey. These results demonstrate that LongScope excels at leveraging extensive references, offering a substantial advantage in tasks that require advanced information integration across large-scale resources.

4.5 Analysis of the Components

The skeleton serves as a pivotal component, acting as a bridge between the digest construction and the final output content. Due to its critical role, it demands more computational resources for refinement. We have devised two mechanisms for harnessing test-time scaling, namely Entropy-Driven



(a) Effect of Convolutional Layer (b) Effect of Convolutional Kernel (c) Effect of Self-Refinement

Figure 5: Analysis of the components in LongScope. We use the normalized information entropy score as the evaluation metric for the skeleton, which reflects the informativeness of the intermediate results.

Convolution and Best-of-N Self-Refinement, with the aim of achieving the desired enhancement. In this section, we will delve into these two modules from the information entropy perspective to analyse the performance under different settings.

Entropy-Driven Convolution In this module, we focus on the Convolutional Layer and the Width of the Convolutional Kernel because of its importance in CNN. With the `top-k` set to six and the `result num` set to ten, we carried out ten layers for each configuration of the convolutional kernel width (ranging from two to six) and computed the averaged normalized values of the information entropy of the generated skeletons across all trials. The relationship between the number of convolutional layers and the scores is shown in Figure 5a, where the experimental results demonstrate that the peak performance occurs at 7 convolutional layers. Additionally, Figure 5b illustrates that the value reaches its maximum when the width is 3 at layer 7. This observation is in accordance with the theoretical design principle: A lack of sufficient layers and a narrow width are unable to capture global contextual information, whereas an excessive number of layers and an overly wide width may lead to the aggregation of redundant information beyond the model's processing capability.

Best-of-N Self-Refinement We question whether simply scaling the number of self-refinements can bring continuous improvements. With convolution-related hyperparameters fixed and `best-of` set to 3, we test and record the information entropy in each self-refined skeleton. As shown in Figure 5c, the peak performance is attained at three self-refined iterations. We can conclude that moderate self-refinement can enhance quality, while excessive self-refinement may lead to deviation from the original material which will cause the deterioration of the skeleton.

5 Related Work

Currently, long-to-long generation methods predominantly rely on extractive approaches. For instance, STORM and Co-STORM (Shao et al., 2024; Jiang et al., 2024) utilize a multi-agent system to formulate questions from diverse perspectives, enabling the retrieval of documents from the Internet for the purpose of authoring a Wiki article. OmniThink (Xi et al., 2025) and the IRP framework (Balepur et al., 2023) enhance the RAG-based method by extracting relevant paragraphs for content writing. Existing end-to-end generation works, such as (Bai et al., 2025), due to the limitations of the model's capabilities, achieving satisfactory results remains challenging.

Specifically, within the domain of survey writing, Wang et al. (2024b) put forward AutoSurvey, a system engineered to automate the process of survey creation via retrieval and iterative refinement. Hu et al. (2024) presented HiReview, which hierarchically clusters paper titles to generate a skeleton used to produce the full survey content. PaSa (He et al., 2025) provide an advanced Paper Search agent. In the current scenario, the consideration of how to integrate vast amounts of information has become increasingly crucial.

6 Conclusion

We introduce LongScope, an integrative framework that leverages entropy-driven convolutional test-time scaling to enhance the ability of LLMs to process and synthesize extremely long input materials. For evaluation, we present SurveyEval, a novel benchmark designed to assess the effectiveness of our method, demonstrating its superiority over existing baselines in generating comprehensive surveys. Our work contributes both to the theoretical understanding and the technical advancements in long-to-long, resource-intensive generation tasks.

Limitations

At present, LongScope has only been verified on the survey task, and in the future, it needs to be extended to more practical tasks, such as research reports. Benefiting from the high cost-effectiveness and high response speed of the Gemini-flash-thinking model, we mainly conducted experiments based on this model. In the future, we will verify the effectiveness of the method on newer and more powerful models, such as DeepSeek-R1. The hallucination of the base model may lead to errors and misleading information in the generated, readers need to distinguish the authenticity of the content.

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A Information Bottleneck in Survey Generation

Let X be the input materials, which include the topic T of the required output article (i.e., Y) and the provided resources R, which may be very lengthy. For intermediate representations, we introduce the skeleton S, aligned with the output Y, and the digests D, which are compressed summaries derived from the resources R. $H(\cdot)$ represents the information entropy, $I(\cdot,\cdot)$ represents the mutual information.

Eq. (1) can be deduced as follow:

$$IB(X,Y) = I(Z;Y) - \beta I(X;Z), \tag{4}$$
$$I(Z;Y) = I(D,S;Y), \tag{5}$$
$$I(X;Z) = I(R,T;D,S). \tag{6}$$

(5) is simplified as follows:

$$I(D,S;Y) = I(S;Y) + I(D;Y|S). \tag{7}$$

(6) is simplified as follows:

$$I(R,T;D,S) = I(T;D,S) + I(R;D,S|T),$$
$$I(T;D,S) = I(S;T) + I(D;T|S), \tag{8}$$
$$I(R;D,S|T) = I(S;R|T) + I(D;R|T,S). \tag{9}$$

Assume that reference papers R include all information of Survey Skeleton S and Paper Digests D, Survey Skeleton S and Paper Digests D include all information of Survey Topic T, and Survey Y include all information of Survey Skeleton S.

(7) is simplified as follows:

$$I(S,Y) = H(S) \tag{10}$$
$$I(D;Y|S) = H(Y|S) - H(Y|D,S) \tag{11}$$
$$H(Y|S) = H(Y) - H(S)$$
$$H(Y|D,S) = H(Y|D)$$

As $I(Y;D) = H(Y) - H(Y|D)$, so (11) can be simplified as follow:

$$I(D;Y|S) = I(Y;D) - H(S) \tag{12}$$

Add (10) and (12), (5) and (7) can be simplified as:

$$I(Z;Y) = I(D,S;Y) = I(Y,D) \tag{13}$$

(8) can be simplified as:

$$I(T;D,S) = I(S;T) + I(D;T|S)$$
$$I(S;T) = H(T)$$
$$I(D;T|S) = H(T|S) = 0$$
$$I(T;D,S) = H(T) \tag{14}$$

(9) can be simplified as:

$$I(R;D,S|T) = I(S;R|T) + I(D;R|T,S)$$
$$I(S;R|T) = H(S|T) = H(S) - H(T)$$
$$I(D;R|T,S) = H(D|T,S)$$
$$H(D|T,S) = H(D) - I(D;T,S)$$
$$I(D;T,S) = H(T,S) = H(S)$$
$$I(R;D,S|T) = H(D) - H(T) \tag{15}$$

Add (14) and (15), Formula (6) can be simplified as follows

$$I(X;Z) = H(D) \tag{16}$$

Add (13) and (17),, we get the result:

$$IB(X,Y) = I(Y,D) - \beta H(D) \tag{17}$$

Based on assumptions, we can get this result:

$$\min(I(Y,D), H(S)) \leq I(Y,D) \leq H(Y,D) \tag{18}$$

It can be concluded the upper and lower bounds of IB, namely:

$$IB(X,Y) \geq \min((1-\beta)H(D) - H(D|Y), H(S) - \beta H(D)),$$
$$IB(X,Y) \leq H(Y|D) + (1-\beta)H(D). \tag{19}$$

B Details of SurveyEval Dataset

B.1 Dataset Construction

The limitations of currently available publicly released survey datasets are evident, as they predominantly include only abstracts of the references, which often lack the detailed information necessary for comprehensive survey-based research. For instance, the *AutoSurvey* dataset (Wang et al., 2024b) does not include any reference relationships, while others, such as *HiCaD* (Hu et al., 2024), focus primarily on the outlines of literature surveys. Additionally, datasets like *NLPCC2024 Shared Task 6* (Tian et al., 2024), *SciReviewGen* (Kasanishi et al., 2023), and *BigSurvey* (LIU et al., 2022) only include abstracts of references, which limits their applicability for more in-depth research tasks.

Moreover, the few datasets that do include full-text references are generally tailored to section generation tasks, and the *SurveySum* dataset (Fernandes et al., 2024) contains only six literature surveys.

Name	Component					Input Length		Data Size	
	Outline	Abstract	Full Text	Refs		Sents. / Token	Avg. Ref.	Survey Num.	Ref Num.
				Abstract	Full Text				
AutoSurvey (Wang et al., 2024b)	✗	✓	✓	✗	✗	–	–	–	530,000
HiCaD (Hu et al., 2024)	✓	✗	✗	✓	✗	471.4 / –	81.1	7,637	619,360
NLPCC2024 Shared Task 6 (Tian et al., 2024)	✗	✓	✓	✓	✗	–	98.5	700	68,950
SciReviewGen (Kasanishi et al., 2023)	✓	✓	✓	✓	✗	– / 12.5k	68	10,130	690,000
BigSurvey (LIU et al., 2022)	✗	✓	✓	✓	✗	450.1 / –	76.3	4,478	341,671
SurveySum (Fernandes et al., 2024)	✓	✗	✓	✗	✓	–	–	6	–
SurveyEval	✓	✓	✓	✓	✓	27.5k / 1383.2k	110.6	384	42,480
SurveyEval-test	✓	✓	✓	✓	✓	40.8k / 2112.0k	179.3	20	3,585

Table 2: Comparison of survey datasets, highlighting key components, input lengths, and data sizes across multiple datasets. The *Component* column shows the inclusion of specific parts in each dataset: *Outline*, *Abstract*, *Full Text*, and references (*Refs*), with the *Refs* column further split into references in the Abstract and Full Text. The *Input Length* section provides the average number of sentences (Sents.) and tokens (Token) per data entry, while *Avg. Ref.* denotes the average number of references per entry. The *Survey Num.* indicates the number of surveys included in the dataset, and *Ref. Num.* reflects the total number of references for the surveys. For datasets without publicly available information, a "–" is used as a placeholder.

To bridge this gap and significantly enhance existing frameworks, we constructed the **SurveyEval Benchmark**. This dataset is designed to contribute to long-to-long generation tasks, which are essential for advancing models' capabilities to handle long-form texts. The SurveyEval dataset is distinctive in its inclusion of both comprehensive literature reviews and **full references**, along with its superior handling of input length.

Our dataset construction process was carefully designed to ensure both data quality and relevance. We obtained academic survey papers by querying the arXiv repository within the `cs.CL` category. After filtering the papers using large language models (LLMs) to determine their suitability as academic surveys, we conducted further searches for their references in reputable sources such as ACL, NeurIPS, CVPR, and Google Scholar. To process the raw PDF data, we utilized `MinerU` (Wang et al., 2024a), an open-source tool developed for the precise extraction of academic content into a structured Markdown format. After data extraction, we employed a two-step quality control process: (1) automated filtering using the `Qwen2.5-72B-Instruct-AWQ-YARN-128k` model (Team, 2024b) to remove low-quality papers, and (2) manual verification to ensure the accuracy and relevance of the content.

For a detailed comparison of the dataset characteristics, refer to Table 2.

B.2 Test Dataset

Generating, evaluating, and manually assessing survey-based algorithms is a time-consuming and resource-intensive process. Given this, the *AutoSurvey* model (Wang et al., 2024b) also uses a test set of 20 papers. Similarly, for this study, we selected 20 papers from the SurveyEval dataset to conduct our research.

To ensure a fair and comprehensive evaluation, we applied two main selection criteria: (1) the completeness of reference retrieval (i.e., the percentage of references successfully obtained from external sources), and (2) the diversity of token counts in the reference lists, ensuring a wide range of input sizes. This approach ensures that our test set is representative of real-world scenarios. Specific details of the dataset can be found in Table 3.

C Implementation Details of Baselines

C.1 Implementation of Vanilla

The vanilla baseline serves as a straightforward approach to literature review generation. This implementation makes direct use of the language model's capabilities by feeding it the survey topic along with the full content of all referenced papers. To address the model's context window limitations while ensuring comprehensive coverage, we apply a proportional text cropping strategy to the reference papers.

C.2 Implementation of Vanilla with skeleton

This baseline improves the survey generation process by adopting a two-stage approach. In the first stage, the model generates a structural skeleton based on the topic and abstracts of all referenced papers. In the second stage, this skeleton is combined with the full text of the referenced articles to produce a comprehensive survey.

Title	Survey Token	Ref. Rate	Ref. Count	Ref. Token
Recent Advances in Direct Speech-to-text Translation	7327	100.00%	23	236824
A Primer on Contrastive Pretraining in Language Processing: Methods, Lessons Learned and Perspectives	8367	100.00%	40	495758
End-to-end Task-oriented Dialogue: A Survey of Tasks, Methods, and Future Directions	12385	100.00%	52	689330
A Survey on Proactive Dialogue Systems: Problems, Methods, and Prospects	8278	100.00%	56	823666
Modern Question Answering Datasets and Benchmarks: A Survey	10240	100.00%	75	1294011
A Survey on Measuring and Mitigating Reasoning Shortcuts in Machine Reading Comprehension	11099	100.00%	106	2058171
A Survey on Recent Advances in Reinforcement Learning for Dialogue Policy Learning	10068	99.07%	107	2123869
A Survey on Explainability in Machine Reading Comprehension	9732	98.44%	125	2069256
Confidence Estimation and Calibration in Large Language Models: A Survey	11311	99.25%	128	2421195
Controllable Text Generation with Transformer-based PLMs: A Survey	20350	98.84%	170	2486701
Measure and Improve Robustness in NLP Models: A Survey	9548	98.33%	177	3257176
Neural Entity Linking: A Survey of Deep Learning Models	35275	98.10%	206	3373014
Machine Reading Comprehension: Contextualized Language Models and Beyond	33695	96.77%	207	4663897
Non-Autoregressive Generation for Neural Machine Translation: A Survey	37197	97.93%	236	4254491
Chain of Thought Reasoning: Advances, Frontiers and Future	18302	95.40%	248	3233452
Bias and Fairness in Large Language Models: A Survey	47372	95.59%	260	677128
Efficient Methods for Natural Language Processing: A Survey	12253	98.94%	280	1119131
The Efficiency Spectrum of Large Language Models: An Algorithmic Survey	19574	94.80%	327	2128935
Pre-trained Language Models in Biomedical Domain: A Systematic Survey	41887	95.76%	351	1426231
Code-Switching Research in NLP: A Systematic Survey on Trends and Challenges	13239	93.76%	411	3408349

Table 3: Test Set Statistics of SurveyEval. The *Survey Token* represents the total length of the literature survey in tokens. The *Ref. Rate* indicates the percentage of references that were successfully retrieved and converted into usable data. The *Ref. Count* refers to the total number of references cited in each literature survey. The *Ref. Token* represents the cumulative token count of all references associated with the literature survey.

C.3 Implementation of AutoSurvey

In this study, we implement AutoSurvey using the test set from SurveyEval (test set details are provided in Appendix B). We follow the original framework while making necessary adjustments to accommodate our testing dataset and evaluation process. All parameter settings are consistent with those specified in the original work.

Data Adaptation. To ensure compatibility with our evaluation framework and dataset, we construct a retrieval database for each survey paper and its corresponding references. Although the number of references in our dataset is fewer than 1,200, we still configure the retrieval to include 1,200 papers to ensure all references can be retrieved, as specified in AutoSurvey. This retrieval process ensures that all references for a survey paper are included in the initial retrieval stage.

Subsection and Outline Generation. The embedding model is `nomic-embed-text-v1`, in line with the original AutoSurvey implementation. All parameters remain unchanged from the original paper. Outline generation is based on the abstracts of the selected papers, as in the original method. For subsection generation, the number of sections is predetermined to be 8. The model processes the first 1,500 tokens from the main body of the 60 relevant papers retrieved, ensuring detailed and coherent descriptions. The same set of reference papers is used throughout the reflection and polishing stages to maintain consistency and accuracy.

C.4 Implementation of LongScope

Here are the important hyperparameters of LongScope:

- convolution_layer = 6, as Digest-Based Feedback Clustering equals to one layer
- kernel_width = 3
- convolution_result _num = 10
- top_k = 6
- self_refine_count = 3
- self_refine_best_of = 3

D Details of SurveyEval Evaluation

Our evaluation framework consists of both automatic and human evaluation components to ensure a comprehensive assessment. To standardize the evaluation across multiple dimensions, we set the score range for all assessments to a 100-point scale. To facilitate an objective comparison with the baseline, we have referenced specific evaluation metrics from AutoSurvey (Wang et al., 2024b). The original automated evaluation metrics include two main components: Content Quality and Citation Quality.

For Content Quality, we retained the criteria of structure and relevance. Since the original scoring used a 5-point scale, we multiplied the raw scores by 20 after obtaining them to enhance differentiation and align the scores with other ranges.

The original coverage score has been refined and is now represented by a more detailed assessment of reference quality. As for Citation Quality,

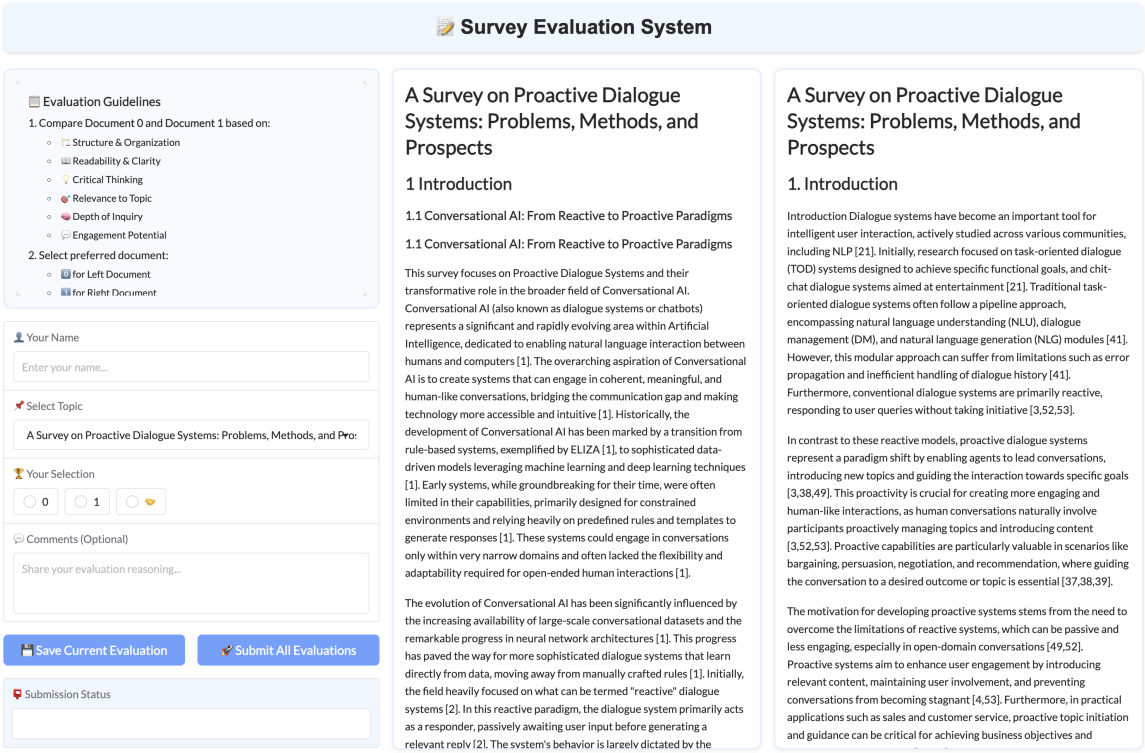

Figure 6: Screenshot of the web application for evaluating the survey pair.

we adapted the evaluation prompt from AutoSurvey (Wang et al., 2024b) for individual citations while modifying and supplementing the calculation methods. Below are the specific criteria and the implementation of the SurveyEval Evaluation:

D.1 Automatic Evaluation criteria

D.1.1 Structure Quality criteria

The structure of the survey is evaluated based on the criteria outlined in AutoSurvey. The score, initially on a scale of 0-5, is multiplied by 20 to align with other score ranges. For the detailed criteria, please refer to Table 4.

D.1.2 Content Quality criteria

For **Faithfulness**, we adopted the prompt from AutoSurvey (Wang et al., 2024b) shown in Fig. 7 to assess citation quality, evaluating the accuracy and relevance of citations within the survey. For the CLAIM component, we mapped citation indices to their corresponding reference papers, conducting separate evaluations for multiple citations to ensure each assessment is associated with only one reference paper. For the SOURCE component, we incorporated the full text of the corresponding reference paper. The detailed Faithfulness is calculated as follows:

$$\text{Faithfulness} = \frac{\sum_{i=1}^{C} \mathbb{I}\left[\sum_{j=1}^{R_{c_i}} h(c_i, r_j)\right]}{C},$$

where R_{c_i} is the number of times paper c_i is cited, C is the number of claims in the survey, and r_j represents the jth cited reference paper of c_i, and

$$h(c_i, r_j) = \begin{cases} 1, & \text{if } r_j \text{ correctly supports } c_i \\ 0, & \text{otherwise} \end{cases}$$

The **Relevance** of the survey is also evaluated based on the criteria from AutoSurvey (Wang et al., 2024b). The score, initially on a scale of 0-5, is multiplied by 20 to align with other score ranges. For detailed criteria, please refer to Table 5.

To provide a more comprehensive evaluation of the quality of the generated literature reviews, we propose two additional evaluation criteria: **Language** and **Criticalness**. Language evaluates the clarity, formality, and redundancy in the writing, ensuring it maintains academic rigour while avoiding unnecessary repetition. Criticalness assesses the depth of analysis, originality of insights, and the identification of future research directions. For detailed scoring standards, please refer to Figure 8 and Figure 9.

Description	Structure: Structure evaluates the logical organization and coherence of sections and subsections, ensuring that they are logically connected.
Score 1	The survey lacks logic, with no clear connections between sections, making it difficult to understand the overall framework.
Score 2	The survey has weak logical flow with some content arranged in a disordered or unreasonable manner.
Score 3	The survey has a generally reasonable logical structure, with most content arranged orderly, though some links and transitions could be improved such as repeated subsections.
Score 4	The survey has good logical consistency, with content well arranged and natural transitions, only slightly rigid in a few parts.
Score 5	The survey is tightly structured and logically clear, with all sections and content arranged most reasonably, and transitions between adjacent sections smooth without redundancy.

Table 4: Structure Evaluation Criteria

```
---
Claim:
[CLAIM]
---
Source:
[SOURCE]
---
Claim:
[CLAIM]
---
Is the Claim faithful to the Source?
A Claim is faithful to the Source if the core part of the Claim can be
supported by the Source.

Only reply with 'Yes' or 'No':
```

Figure 7: Claim evaluation prompt.

D.1.3 Claim Evaluation Details

Claim Numbers Inspired by FactScore's approach to decomposing atomic knowledge (Min et al., 2023), we adapt its methodology to extract effective claims from the paper. Specifically, each section of the survey is treated as an independent unit, with claims extracted separately for each. The extraction process employs a structured, prompt-based approach using the `gemini-2.0-flash-thinking-exp-1219` model, which adheres to specific consolidation rules for claim identification. The extraction prompt enforces strict guidelines, as shown in Fig. 10.

To ensure uniqueness, we implement a two-phase deduplication process. The first phase performs intra-group deduplication on smaller batches (300 claims each), while the second phase conducts cross-group deduplication, deduplicates pairwise and thenmergese them until there is only one group left. Both phases utilize the deduplication criteria outlined in Figure 11. The final claim number is determined based on the total number of claims after deduplication.

Claim Density. Claim Density is defined as the ratio of unique claims to the total number of extracted claims prior to deduplication. This metric serves as a measure of information redundancy in the original text, with a higher density indicating a more efficient presentation of information. The density is computed after both intra-group and cross-group deduplication phases to ensure that only genuinely unique claims are included in the final count. It can be calculated as follows:

$$\text{Claim Density} = \frac{\delta(c_{ij})}{\sum_{i=1}^{S}\sum_{j=1}^{C_i}},$$

where C_i represents the number of claims extracted from section i, S is the total number of sections. c_{ij} represents the jth claim in section i

Description	Relevance: Relevance measures how well the content of the survey aligns with the research topic and maintains a clear focus.
Score 1	The content is outdated or unrelated to the field it purports to review, offering no alignment with the topic.
Score 2	The survey is somewhat on topic but with several digressions; the core subject is evident but not consistently adhered to.
Score 3	The survey is generally on topic, despite a few unrelated details.
Score 4	The survey is mostly on topic and focused; the narrative has a consistent relevance to the core subject with infrequent digressions.
Score 5	The survey is exceptionally focused and entirely on the topic; the article is tightly centred on the subject, with every piece of information contributing to a comprehensive understanding of the topic.

Table 5: Relevance Evaluation Criteria

and $\delta(\cdot)$ is an indicator function that:

$$\delta(\cdot) = \begin{cases} 1, & \text{if } \cdot \text{ is retained as unique} \\ 0, & \text{if } \cdot \text{ is redundant} \end{cases}$$

D.1.4 Reference Evaluation Details

In order to measure the utilization rate of the provided references, two metrics are designed:

Precision measures the coverage of input references by verifying whether each reference is correctly cited at least once. It is calculated as:

$$\text{Ref. P} = \frac{\sum_{j=1}^{R} \mathbb{I}\left[\sum_{i=1}^{C} h(c_i, r_j)\right]}{R},$$

where R is the number of input references, C is the number of sentences with citations in the survey, r_j is the jth reference paper and

$$h(c_i, r_j) = \begin{cases} 1, & \text{if } r_j \text{ correctly supports } c_i \\ 0, & \text{otherwise} \end{cases}$$

Recall evaluates the total number of input references that appear at least once in the generated survey. It is calculated as:

$$\text{Ref. R} = \frac{\sum_{i=1}^{R} c(r_i)}{R},$$

where

$$c(r_i) = \begin{cases} 1, & \text{if } r_i \in R_S \\ 0, & \text{otherwise} \end{cases}$$

and R_S denotes the set of references appearing in the survey.

D.2 Human Evaluation Details

The evaluation process was designed to ensure randomization of topics in order to minimize any potential bias. Evaluators were instructed to select their preferred survey by choosing either "Document 0," "Document 1," or marking "Tie" if both documents were of equal quality. Additionally, evaluators were encouraged to provide comments explaining their choices.

Figure 6 shows a screenshot of the evaluation interface. All results were recorded in real-time and saved for subsequent analysis.

We selected 20 topics from the test set, which were consistent with those used in the automatic evaluation. A total of 17 volunteers from the university were recruited, resulting in 217 valid data points, with the win rate displayed in Figure 4.

```
[Task]
Rigorously evaluate the quality of an academic survey about [TOPIC] by scoring
three dimensions (each 0-100) and calculating the average as the final score.

[Evaluation Criteria]
Evaluate each dimension on a 0-100 scale based strictly on the highest
standards below.  The final score is the average of the three dimension
scores.

1.  **Academic Formality** (100 points):
- Demonstrates *flawless* academic rigor.  Uses precise terminology
consistently, avoids colloquial language entirely, and maintains a strictly
scholarly tone.  Sentence structures are sophisticated and purposefully
crafted to enhance analytical depth.  **Even a single instance of informal
phrasing or imprecise terminology disqualifies a perfect score**.

2.  **Clarity & Readability** (100 points):
- Writing is *exceptionally* clear and concise.  Sentences are logically
structured, with no ambiguity.  Transitions between ideas are seamless, and
the argument progresses with precision.  **Any unnecessary complexity or minor
ambiguity precludes full marks.**

3.  **Redundancy** (100 points):
- **Unique**:  each sentence must have a unique value and cannot be repeated.
Repetition is only allowed to maintain structural coherence, such as using
uniform terminology or necessary transitional phrases.  Repeating key concept
definitions in a new context to help readers understand can be seen as a
structural requirement.
- **Efficient argumentation**:  Argumentation needs to be efficient, with
logically coherent viewpoints and avoiding unnecessary repetition.  Even minor
repetitions without actual structural effects can result in the deduction
of points.  For example, repeating a discovery almost identical in the same
paragraph without providing new insights or perspectives will result in the
deduction of points.

[Topic]
[TOPIC]

[Section]
[SECTION]

[Output Format]
Rationale:
<Provide a detailed reason for the score, considering all dimensions step by
step.  Highlight specific strengths and weaknesses, such as the consistency
of academic tone, the clarity of sentence structure, or the presence of
redundancy.>
Final Score:
<SCORE>(X+Y+Z)/3</SCORE>
(Example:  <SCORE>23</SCORE>; scores can include two decimal place)
```

Figure 8: Language evaluation prompt.

```
[Task]
Rigorously evaluate the quality of an academic survey about [TOPIC] by scoring
three dimensions (each 0-100) and calculating the average as the final score.

[Evaluation Criteria]
The final score is the sum of the individual scores from the following three
dimensions.  Please evaluate each dimension thoroughly and rigorously.

1.  **Critical Analysis** (100 points):
- Offers a deep, incisive critique of methodologies, results, and underlying
assumptions.  Provides a clear identification of significant gaps, weaknesses,
and areas for improvement.  Challenges assumptions with well-supported
arguments, offering clear alternatives or improvements.

2.  **Original Insights** (100 points):
- Proposes novel, well-supported interpretations or frameworks based on the
reviewed literature.  Demonstrates a strong understanding of the subject
matter and provides genuinely original contributions that challenge the status
quo.  Insights are clearly connected to existing research, offering fresh
perspectives or unique ways forward.

3.  **Future Directions** (100 points):
- Clearly identifies specific, promising research directions with strong
justification.  Suggests actionable, concrete ideas for future research
that are rooted in the gaps identified within the reviewed literature.
Demonstrates foresight in proposing innovative approaches and methodologies.

[Topic]
[TOPIC]

[Section]
[SECTION]

[Output Format]
Rationale:
<Provide a detailed reason for the score, considering all dimensions step
by step.  Highlight specific strengths and weaknesses, such as the depth of
critique, the originality of insights, or the clarity of future directions.>
Final Score:
<SCORE>(X+Y+Z)/3</SCORE>
(Example:  <SCORE>23</SCORE>; scores can include two decimal places)
```

Figure 9: Criticalness evaluation prompt.

```
Analyze the following text and decompose it into independent claims following
strict consolidation rules:

[Claim Definition]
A verifiable objective factual statement that functions as an independent
knowledge unit.  Each claim must:
1.  Contain complete subject-predicate-object structure
2.  Exist independently without contextual dependency
3.  Exclude subjective evaluations

[Merge Rules]→ Should merge when:
- Same subject + same predicate + different objects (e.g., "Should measure A /
Should measure B" → "Should measure A and B")
- Different expressions of the same research conclusion
- Parallel elements of the same category (e.g., "A, B and C")

[Separation Rules]→ Should keep separate when:
- Different research subjects/objects
- Claims with causal/conditional relationships
- Findings across temporal sequences
- Conclusions using different verification methods

[Output Format]
Strict numbered list with consolidated claims maintaining grammatical
integrity:
1.  Use "and/or/including" for merged items
2.  Separate parallel elements with commas
3.  Prohibit abbreviations or contextual references

Below is the text you need to extract claims from:

{text}
```

Figure 10: Claim decomposition prompt.

```
Below is a numbered list of claims.  Your task is to identify and group claims
that convey the same information, removing all redundancy.

[Guidelines]
- Claims that express the same fact or knowledge in different wording or detail
are duplicates.
- If one claim is fully included within another or repeats the same idea,
consider it a duplicate.
- Claims with differing details, context, or scope are not duplicates.

For each group of duplicates, output the serial numbers of the claims to be
removed (comma-separated).  Choose one claim to keep.

Example:
If claims 2, 5, and 8 are duplicates and claim 2 is kept, output "5,8".

List of claims:
{numbered_facts}

Output ONLY the serial numbers to remove.  No additional text.
```

Figure 11: Redundancy removal prompt.