MAJI: A Multi-Agent Workflow for Augmenting Journalistic Interviews

Anonymous ACL submission

Abstract

Journalistic interviews are creative, dynamic processes where success hinges on insightful, real-time questioning. While Large Language Models (LLMs) can assist, their tendency to generate coherent but uninspired questions optimizes for probable, not insightful, continuations. This paper investigates whether a structured, multi-agent approach can overcome this limitation to act as a more effective creative partner for journalists. We introduce MAJI, a system designed for this purpose, which employs a divergent-convergent architecture: a committee of specialized agents generates a diverse set of questions, and a convergent agent selects the optimal one. We evaluated MAJI against a suite of strong LLM baselines. Our results demonstrate that our multi-agent framework produces questions that are more coherent, elaborate, and original (+36.9% for our best model vs. a standard LLM baseline), exceeded strong LLM baselines on key measures of creative question quality. Most critically, in a blind survey, professional journalists preferred MAJI's selected questions over those from the baseline by a margin of more than two to one. We present the system's evolution, highlighting the architectural trade-offs that enable MAJI to augment, rather than simply automate, journalistic inquiry. We will release the code upon publication.

1 Introduction

The practice of journalism is a cornerstone of an informed society, with the interview serving as a primary tool for information gathering and narrative construction. While interviews are often prepared with a structured outline, the most compelling insights emerge from unscripted moments. A journalist's ability to react to new information and identify novel angles in real-time separates a standard interview from a revelatory one. This dynamic process, however, presents a significant cognitive load.

Recent advancements in Large Language Models (LLMs) have opened new avenues for assisting in complex, language-based tasks (Touvron et al., 2023; OpenAI et al., 2024). A straightforward approach might involve prompting an LLM with the conversation history and asking for the next question. However, this often yields generic or predictable questions (Gordin et al., 2023), as LLMs tend to optimize for the most probable continuation rather than the most insightful or creative one. Recognizing this limitation, recent research has proposed a range of methods to enhance the originality and depth of LLM-generated interview questions. For example, works such as Spangher et al. (2025), Lin et al. (2025b), and Tian et al. (2024) introduce agentic workflows and creative reasoning strategies to move beyond surface-level responses. Our work builds on this line of research, further exploring how a multi-agent, divergent-convergent architecture can systematically augment the creative process in journalistic interviews.

Formally, this task can be seen as a conditional language generation problem. A standard LLM approach maximizes the likelihood of the next question Q_{t+1} given the transcript history T_t:

$$Q_{t+1} = \arg\max_{Q} P(Q|T_t)$$

This formulation often leads to probable but uninspired responses. We propose reframing the problem as maximizing a utility function $U(Q)$ that captures the goals of journalistic inquiry:

$$Q_{t+1} = \arg\max_{Q} U(Q|T_t, O, P)$$

where utility depends on the question's insight and relevance to the interview's strategic `Outline` O and the interviewee's `Persona` P. MAJI is proposed to address this more complex optimization problem.

To address this gap, we introduce MAJI (Multi-Agent Workflow for Journalism Interview), a sys-

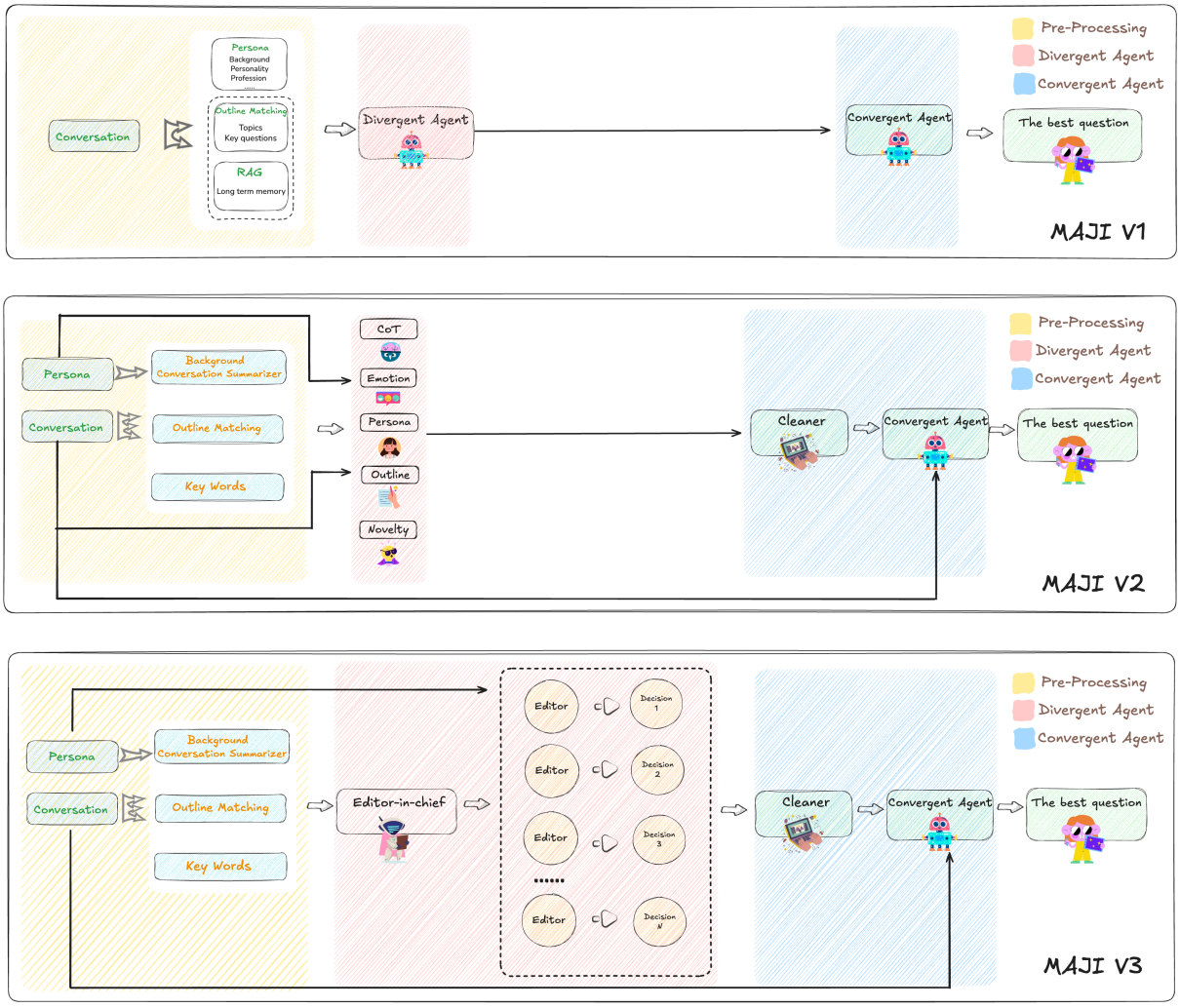

Figure 1: The architectural evolution of MAJI across its three versions. V1 (left) established a simple two-agent divergent-convergent model. V2 (center) introduced a specialized committee of agents for greater diversity. V3 (right) explored dynamic agent generation for adaptive strategies.

tem designed not to replace the journalist, but to augment their creative process. The human-in-the-loop workflow, depicted in Figure 2, positions MAJI as an assistant that provides suggestions while the journalist retains full control. MAJI is built on the psychological principle of divergent-convergent thinking, a cornerstone of creative problem-solving (Guilford, 1950). Our hypothesis is that by decomposing question generation into specialized sub-tasks, a multi-agent system (MAS) can produce more diverse and insightful questions than a single model. The power of MAS has been shown for complex logical tasks (Wooldridge, 2009; Wang et al., 2023; Wu et al., 2023; Qian et al., 2023; Li et al., 2023a), and we apply this paradigm to a creative domain (Lin et al., 2025a; Xi et al., 2025; Zhou et al., 2023; Li et al., 2023b).

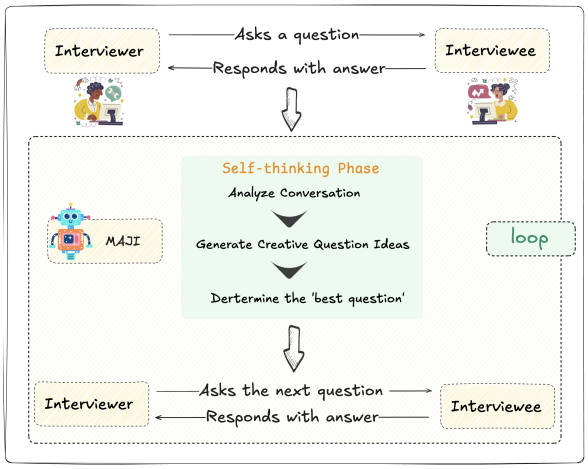

Figure 2: High-level overview of the MAJI-assisted interview workflow. MAJI operates in a continuous loop, observing the conversation and providing question suggestions to the journalist, who retains final control over the direction of the interview.

This paper details the design and evolution of the MAJI framework across three major versions, from a simple proof-of-concept to a sophisticated system capable of dynamically generating its own specialized agents. We conducted a rigorous evaluation using a simulated interview environment inspired by prior work in computational journalism (Diakopoulos, 2019; **?**). Our contributions are threefold:

1. **A Novel Multi-Agent Framework:** We proposed and implemented a divergent-convergent multi-agent architecture for the creative task of interview question generation.

2. **Empirical Evaluation:** We conducted a comprehensive comparison of MAJI against strong LLM baselines, using quantitative, qualitative, and comparative metrics assessed by both LLM-as-judge and professional journalists.

3. **Architectural Insights:** We documented MAJI's evolution, providing insights into the trade-offs between fixed-specialist and dynamically-generated agent committees.

Our findings show that MAJI consistently generates questions that are more insightful, original, and contextually relevant than those from a well-prompted, powerful LLM. This work demonstrates the potential of structured multi-agent systems to move beyond simple automation and act as powerful creative partners in complex professional domains like journalism.

2 Related Work

Prior systems concentrate on data mining, fact checking and bias detection (Cohen et al., 2011; Diakopoulos, 2019; Hamborg et al., 2018), leaving the *real-time* interviewing stage under-explored. Datasets such as *NewsInterview* (Lu et al., 2024) highlight this gap; MAJI directly addresses it by operating live. Techniques like Chain-of-Thought (Wei et al., 2022), Tree-of-Thought (Yao et al., 2023) and retrieval-augmented generation improve single-model reasoning but still rely on one monolithic agent. Multi-agent frameworks such as AutoGen (Wu et al., 2023) and CAMEL (Li et al., 2024) show that dividing labour can yield stronger reasoning; MAJI adapts this insight to creative follow-up generation. Psychology links creativity to alternating idea generation and selection (Guilford, 1950). Agent committees have applied this pattern to storytelling and design (Yao et al., 2019; Li et al., 2023b). MAJI is the first to embed the paradigm in journalistic interviewing and to validate its impact with professional users.

3 The MAJI Framework

MAJI is designed to mirror and support the cognitive workflow of a journalist. The framework is built on several core concepts: foundational inputs that set the stage, a multi-agent system that drives the question generation process, and an iterative loop that allows the system to learn and adapt as the interview progresses.

3.1 Foundational Concepts

The interview process begins with the journalist framing the initial context. This human-in-the-loop step is crucial for grounding the AI's subsequent contributions. Three key pieces of information establish this foundation:

- **Persona:** A detailed profile of the interviewee, including their background, personality, profession, and the primary purpose of the interview. This is crafted by the journalist to guide the system's interaction style. For example, a persona for a professional mermaid performer might highlight their artistic motivations and physical challenges, shaping questions toward these themes.

- **Outline:** A structured list of topics and key questions that the journalist intends to cover. This serves as the strategic backbone of the interview, ensuring coverage of critical areas while allowing flexibility for emergent insights.

- **Dynamic Background Summary:** To track evolving context, MAJI uses a dedicated agent to maintain a `BackgroundSummary`. It has a `long_term_summary` for foundational information (e.g., interviewee's career trajectory) and a `short_term_summary` for the last five conversational turns. This provides all agents with a continuously updated, concise view of the conversation history.

These inputs ensure MAJI remains grounded in the journalist's objectives and the interview's evolving context, enabling questions that are both strategically aligned and responsive to in-session dynamics.

3.2 The Divergent-Convergent Workflow

The core of MAJI is an implementation of the divergent-convergent thinking model, executed by specialized agents in a multi-stage workflow. This process, detailed for our primary MAJI V2 system in Algorithm 1, ensures a balance between creative exploration and strategic focus. MAJI's architecture operationalizes this principle. A committee of specialized *divergent agents* brainstorms potential questions, each focusing on a distinct creative vector, such as emotional depth, causal reasoning, adherence to the interviewee's persona, or pure novelty. Their suggestions are then processed by an *Editor Agent* to refine and deduplicate the pool of ideas. Finally, a *convergent agent*, acting as an Editor-in-Chief, selects the single best question that aligns with the conversation's flow and the journalist's strategic goals for the interview. The key stages are:

Algorithm 1 MAJI V2 Question Generation Workflow

Input: Outline O, Persona P, Transcript T
Output: Next question Q
$S \leftarrow \text{BackgroundAgent}(T, P)$ ▷ Update summaries
$K \leftarrow \text{KeywordsAgent}(T, S)$ ▷ Extract keywords
$M \leftarrow \text{OutlineMatcherAgent}(O, T)$ ▷ Map to outline
$C \leftarrow \emptyset$ ▷ Initialize candidate pool
for each DivergentAgent_i in $\{\text{D}_1, \ldots, \text{D}_n\}$ **do**
    $C_i \leftarrow \text{DivergentAgent}_i(K, S, M, P)$ ▷ Propose questions
    $C \leftarrow C \cup C_i$
end for
$C' \leftarrow \text{EditorAgent}(C)$ ▷ Refine candidates
$Q \leftarrow \text{ConvergentAgent}(C', T, P, O)$ ▷ Select optimal question
return Q

1. **Context Analysis (Pre-Divergence):** Before any new questions are brainstormed, a set of pre-processing agents analyzes the latest turn in the conversation to establish a shared understanding of the current state. This includes the `BackgroundAgent` updating the long- and short-term summaries, the `KeywordsAgent` extracting the most salient terms from the latest response, and the `OutlineMatcherAgent` assessing which parts of the interview outline have been covered.

2. **Divergent Thinking:** With the updated context, the committee of specialized divergent agents generates a wide range of potential follow-up questions in parallel. This parallel, specialized approach is designed to produce a candidate pool with high "Flexibility," ensuring a rich set of creative options.

3. **Editing & Curation:** The raw list of questions from the divergent phase is often redundant. The `EditorAgent` uses sentence-transformer embeddings to identify and merge semantically similar questions (similarity threshold: 0.85). This step curates a clean, concise list of unique candidate questions.

4. **Convergent Selection:** Finally, the `ConvergentAgent` takes the curated list of questions and, guided by the journalist's stated strategic preference, selects the single best question to ask next. This selection process is not based on arbitrary heuristics, but on an implicit model of journalistic utility, as detailed below.

3.2.1 Convergent Utility Maximization

The core of the convergent step is the maximization of a utility function U. Rather than being a simple, hard-coded formula, this function is a conceptual model of question quality that the `ConvergentAgent` is prompted to approximate. We can formally define this utility for a candidate question $Q \in C'$ as a weighted sum of scores from various quality dimensions:

$$U(Q|\cdot, S_p) = \sum_{i=1}^{N} w_i(S_p) \cdot \phi_i(Q|T_t, O, P)$$

where each component represents a desirable attribute of a question:

- $\phi_i(Q|\cdot)$ are scoring functions that evaluate different facets of a question's quality, such as its *coherence*, *emotional depth*, *outline progression*, *persona alignment*, and *novelty*. These facets directly correspond to the specializations of the divergent agents.

- $w_i(S_p)$ are weights that are dynamically modulated by the journalist's `Strategic Preference` S_p. For example, if the journalist sets the preference to "focus on emotion,"

the weight w_{emo} for the emotional depth score ϕ_{emo} is implicitly increased. If the preference is "balanced," the weights are distributed more evenly.

In our implementation, the `ConvergentAgent` (a powerful LLM) does not compute explicit scores. Instead, it performs a holistic evaluation, directly approximating the $\arg\max$ operation by using the strategic preference S_p to guide its selection from the candidate set C'. The prompt instructs it to "select the single best question" that "aligns with the preference," effectively performing this weighted optimization. This leverages the LLM's nuanced reasoning to model the complex utility of a journalistic question.

This structured workflow ensures that the final question is not merely a probable continuation, but a strategically selected option from a creatively diverse and well-curated set of possibilities.

4 System Architecture and Evolution

The MAJI framework was developed and refined over three major versions. Each version represents a significant step in the architectural design, moving from a simple proof-of-concept to a highly sophisticated and dynamic system. In essence, these versions can be viewed as a theoretical ablation study, with each successive version adding architectural complexity to examine its impact on performance.

4.1 MAJI V1: A Foundational Proof-of-Concept

MAJI V1 served as a minimal proof-of-concept for the divergent-convergent idea (Figure 1). It used a `DAgent` to generate questions with a single, broad LLM prompt and a `CAgent` that used hard-coded, non-LLM heuristics for selection. This rigid logic struggled with the fluid nature of interviews, highlighting the need for the more nuanced, context-aware reasoning of V2's specialized agent committee.

4.2 MAJI V2: The Specialized Agent Committee

MAJI V2, our best-performing model, implements a robust "agent committee" architecture (Figure 1). The workflow, detailed in Section 3.2, begins with pre-processing agents establishing context. Then, a fixed committee of five specialized divergent agents (`ChainOfThought`, `Emotion`, `Outline`, `Persona`, and `Novelty`) brainstorms questions in parallel. An `EditorAgent` refines the question pool, and a `ConvergentAgent` selects the best question based on the journalist's preference. This specialization proved highly effective at generating rich and diverse candidate questions. An example is in Appendix A.1.

4.3 MAJI V3: Dynamic Agent Generation

MAJI V3 is an experimental evolution that dynamically devises its own interview strategy (Figure 1), where an agent plans the divergent phase. The key innovation is the introduction of an agent that plans the divergent phase itself. The V3 architecture modifies the divergent step:

1. The fixed committee of divergent agents is removed.

2. A new agent, the `EditorInChiefAgent`, is introduced. Based on a set of pre-defined heuristics, its role is to analyze the full conversation context and devise a *plan* for the divergent phase, as defined in our V3 data models.

3. This plan takes the form of a `DivergentAgentPlan`, which contains a list of `DivergentAgentSpec` objects. Each spec defines the `name` and `instructions` for a temporary, single-use divergent agent tailored to the immediate needs of the conversation. For example, if the interviewee seems evasive, it might create a "Probing_Clarification_Agent." If the conversation is stalling, it might create a "Hypothetical_Scenario_Agent."

4. The system then dynamically instantiates these agents from the specs and runs them in parallel to generate questions.

The rest of the pipeline is unchanged. V3 is more autonomous, with the LLM defining generation strategy. However, this complexity introduced challenges. The `EditorInChiefAgent`'s heuristic-based approach is a limitation, and its performance did not surpass V2. A specific example is in Appendix A.2.

5 Evaluation

We designed a comprehensive evaluation framework to assess the performance of the MAJI system. The evaluation aims to answer three key questions:

1. How does MAJI's question generation quality compare to a strong, conventionally-prompted LLM baseline across a diverse dataset?
2. How does the architectural choice (fixed vs. dynamic agent committee) impact performance between MAJI V2 and V3?
3. What are the specific strengths and weaknesses of each system, particularly regarding the trade-off between creativity and conversational coherence?

5.1 Experimental Setup

We evaluated MAJI against strong baselines on real-world interviews from the *NewsInterview* dataset and proprietary sources. All systems used `gpt-4.1-mini`. Baselines included `LLM-Base`, `LLM-CoT`, `LLM-ToT`, and `LLM-RAG`. We used Prometheus 2 for validation and adjusted originality scores with a threshold-based method for realism. Further details are in Appendix A.3.

5.2 Metrics

Our evaluation uses a combination of metrics calculated per-question and per-interview, averaged across the dataset.

5.2.1 Per-Question Metrics

These metrics are evaluated for each generated question. Our primary judge (GPT-4o) scored questions on six criteria: **Coherence** (logical connection), **Elaboration** (encouraging detailed responses), **Originality** (novelty), **Context Relevance** (relation to the last turn), **Outline Relevance** (alignment with the interview plan), and **Persona Alignment** (matching interviewee character). Our benchmark judge (Prometheus 2) provided scores for similar criteria, adding measures for **Insight** (probing deeper), **Conversational Synthesis** (integrating prior conversation), and **Strategic Progression** (advancing interview goals).

To better assess originality, we used a threshold-based adjustment. Since cosine similarity scores for semantically different questions are often non-zero, raw scores can be misleading. Our method uses a 0.6 threshold; similarities below this are scored as 1.0 (completely original), and the rest are scaled. This yields more realistic originality scores while preserving relative rankings.

5.2.2 Per-Interview Metrics

To assess overall strategic performance, we calculated the **Insight Trajectory**, measuring if a system asks more insightful questions in the second half of an interview compared to the first.

6 Results

Our comprehensive evaluation demonstrates the effectiveness of the MAJI framework. We presented a detailed comparison of all MAJI versions and a suite of strong LLM baselines, with results aggregated across the evaluation dataset. The following sections analyze the quality of the final selected questions, the raw brainstormed suggestions, and the strategic performance of each model.

6.1 Primary Analysis: Selected vs. Brainstormed Quality

Our primary evaluation (Table 1) shows that the final questions selected by MAJI V2 and V3 are significantly higher quality than baselines, excelling on metrics like **Coherence**, **Elaboration**, **Originality**, and **Context Relevance** ($p < 0.001$).

This high quality results from our divergent-convergent design. Analysis of the raw brainstormed suggestions (Appendix A.4, Table 3) reveals the convergent agent adds significant value. For MAJI V2, the selection process improves **Coherence** (+9.2%) and **Context Relevance** (+17.6%), showing it successfully elevates the most promising ideas from a diverse but noisy pool. The adjusted originality scores show MAJI V2 achieves the highest originality (0.764), a 36.9% improvement over baseline, while maintaining strong performance elsewhere.

6.2 Benchmark Validation: Prometheus Evaluation

The Prometheus 2 benchmark (Table 2) strongly corroborates our primary analysis. MAJI V2 and V3 again emerge as top performers. Improvements over LLM-Base are statistically significant for key creative metrics like **Insight**, **Originality**, and **Elaboration** ($p < 0.001$ for MAJI V2/V3). MAJI V2 and V3 also score highest in **Outline Relevance** ($p < 0.001$), indicating their questions are both insightful and effective at advancing the interview. This independent verification confirms MAJI's superior performance is a robust, statistically significant result. Prometheus's assessment also validates our adjusted originality scores, with MAJI V2 achieving a 25.1% improvement over baseline. Interestingly, Prometheus rated V1 much lower than our primary judge, suggesting V1's quality is more subjective.

Table 1: Evaluation of Final Selected Questions (Judged by GPT-4o). This table shows the quality of the single question chosen by each system to be asked next. All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * p < 0.05, ** p < 0.01, *** p < 0.001. MAJI V2 and V3 excel in generating high-quality, elaborate, and original questions. Originality scores have been adjusted using a threshold-based method to account for baseline similarity between questions. Best score in each category is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	0.768***	**0.795*****	0.791***	0.704	0.701	0.770***	0.735***
Elaboration	0.861	0.928***	**0.932*****	0.871	0.873	0.901***	0.871
Originality	0.641***	**0.764*****	0.736***	0.558	0.586***	0.666***	0.611***
Context Relevance	0.372***	**0.434*****	0.414***	0.319	0.319	0.373***	0.328
Outline Relevance	**0.779*****	0.656	0.661	0.670	0.673	0.668	0.658*
Persona Alignment	0.838***	0.868	0.865	0.874	**0.880**	**0.880**	0.872

Table 2: Benchmark Evaluation of Final Selected Questions (Judged by Prometheus 2). This table shows scores from a standardized, third-party model, validating the primary results. All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * p < 0.05, ** p < 0.01, *** p < 0.001. Best score is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	0.622	**0.780*****	0.771***	0.629	0.648	0.762***	0.631
Elaboration	0.754	0.898***	**0.908*****	0.774	0.822***	0.839***	0.793
Originality	0.613	**0.733*****	0.727***	0.586	0.584	0.654***	0.608
Context Relevance	0.697*	0.818***	**0.870*****	0.635	0.676	0.807***	0.659
Outline Relevance	0.454	0.586***	**0.624*****	0.417	0.485***	0.589***	0.425
Insight	0.645	0.815***	**0.835*****	0.688	0.741*	0.783***	0.703
Conversational Synthesis	0.581***	**0.743*****	0.739***	0.664	0.697*	0.730***	0.691
Persona Alignment	0.693***	0.837	**0.861*****	0.821	0.835	0.813	0.802

6.3 Human and Strategic Evaluation

We also conducted a human evaluation with 30 professional journalists and analyzed each system's strategic performance. Journalists preferred MAJI V2's questions nearly half the time (48.9%), more than double the rate of the baseline. Furthermore, analysis of the "Insight Trajectory" showed that MAJI V1 had the highest rate of improvement over an interview (Table 8). While MAJI V2 and V3 started from and maintained a much higher insight baseline, V1's simpler architecture appeared effective at building conversational momentum. Full details are in Appendix A.5.

7 Discussion

The results of our experiments provide several key insights into the design of AI systems for creative professional domains.

7.1 The Power of Specialization

The stark performance difference between MAJI V2/V3 and even advanced LLM baselines validates our core hypothesis: decomposing a complex creative task into specialized sub-tasks yields superior results. While advanced prompting like Tree-of-Thought improves LLM performance, MAJI V2's architecture, with dedicated agents for emotion, logic, and novelty, consistently produced questions judged as more insightful and original by both AI and human experts. The adjusted originality scores show MAJI V2 achieves a 36.9% improvement over baseline on the NewsInterview dataset (0.764 vs 0.558) and a 44.1% improvement on the proprietary dataset (0.608 vs 0.422). This cross-dataset consistency across languages validates that the multi-agent architecture's benefits are not domain-specific but a fundamental advantage. This suggests for creative augmentation, a specialized multi-agent architecture is more promising than prompting strategies for single models.

7.2 The "Creative Partner" vs. "Coherent Assistant"

A crucial finding is the trade-off between creative value and conversational coherence. The baseline LLMs, optimized for next-token prediction, naturally excel as Coherent Assistants.

MAJI, conversely, acts as a creative partner. It is less constrained by the most probable con-

versational path and more focused on generating high-quality, novel, and insightful questions. The strong preference from professional journalists underscores the value of this approach; they want a tool that expands their creative options, not just one that affirms their instincts. This focus on quality comes at a computational cost, representing a trade-off between speed and insight (see Appendix A.7).

7.3 Error Analysis

Although MAJI's architecture explicitly avoids redundancy, we observe a trade-off between creativity and relevance. Divergent agents occasionally produce off-topic or abstract suggestions. This is by design, as it broadens potential questioning paths, even if many are discarded.

7.4 V3 and the Challenge of Meta-Cognition

MAJI V3's experiment in dynamic agent generation provides insight into the challenges of AI meta-cognition. While this approach produced highly novel and relevant questions, it was less consistent than MAJI V2. The preference for V2 in our human evaluation suggests that for professional use, V2's reliable creativity is currently more valuable than V3's experimental novelty. This highlights a key challenge: building an agent that can effectively strategize about creative strategy is a difficult, higher-order task. For now, a carefully designed, fixed architecture is more robust. While V3's dynamic agent generation is heuristic-based, this is a necessary stepping stone in creative domains where learning-based planning is an open challenge.

7.5 Broader Implications for Human-AI Creative Partnerships

MAJI's principles are not limited to journalism. The divergent-convergent framework, with specialized agent committees, is a generalizable template for augmenting human creativity in any domain involving iterative ideation and strategic selection. Applications could include helping scientists brainstorm hypotheses, assisting marketing teams with slogans, or helping attorneys explore case strategies. This work contributes to a broader vision of AI not as a replacement for human intellect, but as a structured tool for amplifying it.

8 Conclusion

We introduced MAJI, a multi-agent system to assist journalists by generating creative and insightful interview questions. We demonstrated that by decomposing this task into a divergent-convergent workflow with specialized agents, MAJI moves beyond standard and advanced LLM prompting. Our results, validated by 30 professional journalists, show that our best version, V2, produces questions consistently preferred over strong baselines. In a blind survey, journalists chose MAJI V2's suggestions at more than double the rate of a standard baseline, confirming its superior alignment with professional judgment.

We have shown that a structured, multi-agent architecture is highly effective for augmenting complex, creative human tasks, trading a small amount of predictability for a significant gain in insight and originality. The success of MAJI V2's "agent committee" provides a promising model for building AI-powered creative partners that help professionals overcome cognitive fixation and explore a wider possibility space. The experimental V3, while less performant, offered valuable insights into developing more autonomous, strategy-devising systems, highlighting a clear path for future research. The code, data, and models will be open-sourced to encourage further research.

Limitations

While this study provides strong evidence for MAJI's effectiveness, we acknowledged several limitations that provide avenues for future work. First, our evaluation is conducted on a dataset of professionally curated interviews. The system's robustness on noisier, out-of-domain data—such as unedited live transcripts or interviews on highly specialized topics—remains to be tested. Second, as our qualitative analysis of V3's failure case demonstrates, the system can occasionally produce awkward or contextually inappropriate suggestions. A more detailed qualitative error analysis would be beneficial for identifying and mitigating these failure modes. Our originality metric has been improved through a threshold-based adjustment method to account for baseline similarity between questions, but could be further enhanced to better distinguish semantic novelty from lexical paraphrasing. Third, the latency of the MAJI system, particularly V2 and V3, is a significant consideration (see Appendix A.7). While we argue this is a justifiable trade-off for question quality, further optimization is required to make the system more responsive.

Although a learning-based planner may offer better adaptability in theory, the lack of structured supervision and reward signals in open-ended domains like interviewing makes such training infeasible at present. We therefore use heuristic planning as an exploratory first step in operationalizing strategic meta-reasoning in creative workflows.

Building on these points, future work will focus on expanding our evaluation to broader datasets, refining V3's heuristic planner into a learning-based agent (e.g., using techniques like verbal reinforcement learning (Shinn et al., 2023) or RLHF (Christiano et al., 2017)), conducting component-wise ablation studies to quantify each agent's contribution, developing a real-time user interface for live interviews, and performing a systematic qualitative error analysis to guide future improvements. Future work should also explore model distillation to create smaller, faster versions of the agents, caching strategies for recurring sub-problems, and asynchronous processing to reduce the perceived latency for the user.

Ethical Considerations

The deployment of AI tools like MAJI in journalism necessitates careful consideration of ethical implications. First, there is a risk that the underlying LLM could introduce subtle biases into the question generation process, potentially reflecting political or confirmation biases from its training data and steering conversations in unintended directions. We suggested ongoing monitoring and fine-tuning with diverse datasets to mitigate this. Second, while MAJI is designed to augment, not replace, the journalist, there is a risk of over-reliance, which could diminish the journalist's critical thinking and rapport-building skills. The system should be framed as a supportive tool, with the final decision always resting with the human journalist, who must also approve any intermediate strategic pivots suggested by the AI. Finally, the privacy and consent of the interviewee are paramount. All data used for training and running the system must be handled with explicit consent and robust anonymization procedures, as was done in this study (Alzoubi et al., 2024).

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During the preparation of this work, the authors utilized an AI-powered tool to assist with programming, text editing, and formatting. All AI-generated content, including code and text, was carefully reviewed, revised, and validated by the authors to ensure its accuracy and alignment with the research goals.

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A Appendix

A.1 MAJI V2 Specialization Example

To illustrate the power of specialization in the MAJI V2 committee, consider a response from a professional mermaid performer: *"When I'm down there, everything goes silent. It's just me and the water, and sometimes I forget there's an audience. It's a very physically demanding job, but the peace I feel is worth it."*

The specialized divergent agents might respond as follows:

- `EmotionDivergentAgent`: "You mentioned a feeling of 'peace.' Can you describe the contrast between that inner peace and the intense physical demands of the job?"
- `ChainOfThoughtDivergentAgent`: "What specific physical training was required to allow you to reach that point where you can find peace despite the physical exertion?"
- `PersonaDivergentAgent`: "As an artist, how does that feeling of solitary peace underwater influence the performance that the audience eventually sees?"
- `NoveltyDivergentAgent`: "If you could perform in any body of water in the world, real or mythical, where would you choose to best capture that feeling of peace?"

This example shows how the agent committee generates a rich, multi-faceted set of candidate questions, giving the journalist a far more powerful set of options than a single, generic follow-up.

A.2 MAJI V3 Failure Case Example

The increased autonomy of MAJI V3's dynamic agent generation, while powerful, could sometimes lead to strategic missteps. For example, in an interview with a climate scientist who briefly mentioned enjoying hiking early in the conversation, a dynamically generated 'Personal_Connection_Agent' later interrupted a dense discussion on carbon sequestration models to ask, "You mentioned hiking—what's the most beautiful trail you've ever been on?" While a valid question in isolation, its poor timing demonstrated a failure in strategic conversational awareness—a key failure case for V3's heuristic planner, which occasionally struggled to weigh the global strategic context against a locally-optimized creative idea.

A.3 Experimental Setup Details

- **Dataset:** The evaluation was conducted on a combined corpus from the public *NewsInterview* dataset (entirely in English) and proprietary transcripts from a media tech company (70% Chinese, 30% English). This multilingual setup was designed to test the robustness of the MAJI framework across different languages. The public dataset was filtered to include only those conversations with exactly two speakers and more than 50 conversational exchanges to focus on substantial, dyadic conversations suitable for our framework. The proprietary dataset includes interview transcripts with detailed personas and outlines. This combined dataset contains professionally conducted interviews covering a diverse range of topics, from profiling a professional mermaid performer to discussing political opinions on U.S. elections. This provides a diverse and realistic set of conversational contexts for the systems to respond to, moving beyond a single-interview analysis. Since the public NewsInterview dataset does not include structured outlines, we used GPT-4o to generate a plausible outline for each of these interviews based on the full transcript content. These generated outlines were then provided to all systems.
- **Inputs:** For each turn in every interview, the systems were provided with the same set of inputs: the interviewee's `Persona`, the interview `Outline`, and the full conversation `transcript` up to that point.
- **Models:** All agent systems (MAJI V2, V3) and the baseline systems use `gpt-4.1-mini` as the underlying LLM to ensure a fair comparison of architectural benefits versus model capabilities.
- **Baselines:** We compared MAJI against a suite of strong baselines representing common and advanced prompting techniques:
  - **LLM-Base:** A single, well-prompted call to the base LLM, including the full context.
  - **LLM-CoT:** A baseline using Chain-of-Thought prompting (Wei et al., 2022) to encourage step-by-step reasoning before generating a question.
  - **LLM-ToT:** A baseline using a Tree-of-Thought approach (**?**), where the model explores multiple reasoning paths.
  - **LLM-RAG:** A baseline augmented with a Retrieval-Augmented Generation mechanism. This system uses a sentence-transformer model to find and retrieve the most semantically similar turns from earlier in the same conversation, providing the LLM with relevant long-term context that might have been lost.

- **Benchmark Judge (Prometheus 2):** To validate our findings against a standardized, third-party metric, we also used Prometheus 2, a state-of-the-art open-source evaluation model (Kim et al., 2024). This "black-box" judge acts as an impartial adjudicator, scoring the final selected question from each system. Using a benchmark judge mitigates the risk of "own-model-bias" and strengthens the credibility of our results. Its distinct metrics, such as *conversational synthesis* and *strategic progression*, also provide a valuable alternative perspective on performance.

- **Baseline Prompts**: The core instruction for all baselines was: "You are an expert journalist. Based on the provided Persona, Outline, and Transcript, generate the best possible next question to ask. Your goal is to be insightful, creative, and strategic." For CoT and ToT, additional instructions for step-by-step reasoning and exploring alternatives were included based on their respective papers.

A.4 Full Brainstormed Suggestions Results

Table 3 shows the average quality of the entire pool of questions generated by the divergent phase of each system, before any filtering or selection occurs. This provides a measure of the raw creative output of each architecture.

A.5 Human and Strategic Evaluation Results

A.5.1 Human Evaluation: The Professional's Choice

To complement our automated metrics, we conducted a qualitative survey with 30 professional journalists from a media tech company, all with over five years of experience and a focus on online media. Participants were presented with 25 conversational snippets. These snippets were randomly drawn from 5 interviews, themselves randomly selected from the NewsInterview portion of our dataset. For each snippet, the journalists were provided with the full conversational context up to that point, as well as the interviewee's Persona and the interview Outline to ensure they had the same information as the AI systems. For this study, we report preference shares as the primary outcome. While inter-annotator agreement metrics like Fleiss' Kappa are valuable for tasks with objective ground truths, their interpretation is less straightforward for subjective, creative-preference tasks where there is no single 'best' answer. Therefore, we did not compute IAA for this study, but note that future work using a rated scale (e.g., 1-5) instead of a forced choice could more meaningfully incorporate such agreement analyses.

Participants were asked a forced-choice question: "If you were the interviewer, which question would you have chosen to ask next?" This study provides strong evidence of MAJI's value and usability for professional journalists. The results (Table 7) show a decisive preference for MAJI V2, which was chosen nearly half the time.

A.5.2 Insight Trajectory: Improving Over Time

Beyond the quality of individual questions, we analyzed each system's ability to improve its performance over the course of an interview (Table 8). The results highlight an interesting trade-off. MAJI V1 demonstrated a remarkable ability to improve its insight score, achieving a statistically significant 39.0% improvement rate—far surpassing all other models. Conversely, while MAJI V2 and V3 show smaller relative improvement, this is because they start from a much higher performance baseline. MAJI V3 achieves the highest absolute insight scores in the second half of the interview, a statistically significant improvement over the baseline ($p < 0.01$). Their sustained high quality underscores their superiority, even if their rate of improvement is less dramatic.

A.6 Dataset Topics

The two datasets used in our evaluation cover a wide range of subjects, providing a robust testbed for our system.

NewsInterview Dataset Topics

The topics in the public *NewsInterview* dataset span a broad range of journalistic beats. The main categories are summarized in Table 9.

Proprietary Dataset Topics

The proprietary dataset from the media tech company contains interviews with a more personal and narrative focus. The topics are summarized in Table 10.

Table 3: Evaluation of All Brainstormed Suggestions (Judged by GPT-4o). This table shows the average quality of the entire pool of questions generated by the divergent phase, before any selection occurs. All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This measures the raw creative output. Originality scores have been adjusted using a threshold-based method. Best score is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	**0.808*****	0.728***	0.702*	0.682	0.679	0.704***	0.702***
Elaboration	0.873	**0.899*****	**0.899*****	0.863	0.871**	0.881***	0.863
Originality	0.745***	**0.745*****	0.705***	0.592	0.599	0.635***	0.621***
Context Relevance	**0.387*****	0.369***	0.343***	0.298	0.296	0.313***	0.304*
Outline Relevance	0.658	0.635***	0.665	0.659	0.670***	**0.672*****	0.655
Persona Alignment	0.846***	0.870*	0.873*	0.881	**0.884**	0.882	0.880

Table 4: LLM-as-Judge Evaluation of All Brainstormed Suggestions on Proprietary Dataset. All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Originality scores have been adjusted using a threshold-based method. Best score is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	**0.768*****	0.676*	0.571	0.618	0.610	0.632	0.662***
Elaboration	0.873	**0.905*****	0.891***	0.860	0.869	0.865	0.850*
Originality	**0.547*****	**0.547*****	0.488***	0.395	0.383	0.428*	0.462***
Context Relevance	**0.367*****	0.356***	0.288	0.287	0.280	0.300	0.320***
Outline Relevance	0.655	0.637***	0.647**	0.675	**0.683*****	0.680	0.663
Persona Alignment	0.759***	0.808	0.804	**0.814**	0.812	0.795***	0.795

Table 5: LLM-as-Judge Evaluation of Final Selected Questions on Proprietary Dataset. All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Originality scores have been adjusted using a threshold-based method. Best score is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	0.740	**0.820****	0.723*	0.688	0.725***	0.780***	0.767***
Elaboration	0.874	**0.953****	0.925***	0.875	0.890*	0.890*	0.871
Originality	0.432	**0.608*****	0.561***	0.422	0.455*	0.534***	0.512***
Context Relevance	0.348	**0.430****	0.380	0.351	0.368	0.411***	0.391*
Outline Relevance	**0.761****	0.618*	0.635**	0.668	0.666	0.645*	0.650
Persona Alignment	0.746	**0.834**	0.786**	0.823	0.823	0.811	0.803

Table 6: Benchmark Evaluation of Final Selected Questions on Proprietary Dataset (Judged by Prometheus 2). All models are compared against the LLM-Base baseline. Significance from a two-tailed t-test is denoted by asterisks: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Best score is in **bold**.

Metric	MAJI V1	MAJI V2	MAJI V3	LLM-Base	LLM-CoT	LLM-ToT	LLM-RAG
Coherence	0.503	**0.734*****	0.674	0.591	0.597	0.690*	0.646
Elaboration	0.687	**0.872***	0.860*	0.759	0.768	0.775	0.754
Originality	0.534	0.570	**0.588***	0.536	0.538	0.526	0.469
Context Relevance	0.621	**0.864*****	0.703	0.639	0.655	0.740	0.652
Outline Relevance	0.459	**0.658**	0.639	0.599	0.591	0.654	0.566
Insight	0.552	**0.802***	0.748*	0.672	0.701	0.675	0.618
Conversational Synthesis	0.280	**0.530***	0.402	0.390	0.388	0.420	0.335
Persona Alignment	0.378	**0.590***	0.525	0.496	0.545	0.512	0.462

Table 7: Human Journalist Preference. Results from a blind survey of 30 professional journalists asked to choose the best question from MAJI V2, MAJI V3, and a representative LLM Baseline across 25 conversational snippets.

System	Preference Share (%)
MAJI V2	**48.9%**
MAJI V3	29.5%
LLM Baseline	21.6%

Table 8: Insight trajectory. Average insight scores in the first and second halves of interviews. Significance vs. LLM-Base: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

System	Initial	Final	Improvement (%)
MAJI V1	2.11^{***}	2.60	**39.02**
MAJI V2	2.57	3.02^{*}	29.57
MAJI V3	**2.62**	$\mathbf{3.05}^{**}$	25.47
LLM-RAG	2.48	2.62	17.82
LLM-Base	2.56	2.76	18.07
LLM-ToT	2.48	2.83	31.01
LLM-CoT	2.52	2.83	22.96

Table 10: Topics in the Proprietary Interview Dataset.

Category	Description
Social & Personal Issues	Personal narratives, family dynamics, and cultural identity.
Health & Wellness	Experiences with the healthcare system and personal well-being.
Professional Life	Career paths, workplace experiences, and industry insights.
Disaster & Adversity	Personal accounts of overcoming natural disasters or adversity.

Table 9: Topics in the NewsInterview Dataset.

Category	Description
Politics & Government	U.S./international politics, elections, impeachment, and national security.
Economy, Trade, & Employment	International trade, economic crises, financial regulation, and employment.
Law, Justice, & Human Rights	Criminal justice, human rights issues, press freedom, and whistleblowing.
Health & Social Issues	Healthcare policy, gun control, gender/racial issues, and social dynamics.
Climate, Env., & Disasters	Climate change, disaster management, conservation, and environmental policy.
Arts, Culture, & Literature	Literature, poetry, music history, philosophy, and cultural identity.
Science, Tech., & Education	Biology, astrophysics, engineering, internet technology, and education.
Sports & Ethics	Professional sports, commentary, and ethical debates in sports.

A.7 Latency Analysis

MAJI V2 requires an average of 16.59 seconds per question, compared to 1.42 seconds for baseline models. This higher latency reflects MAJI's sequential, multi-agent architecture, which explicitly trades speed for strategic depth. Unlike single-shot LLMs, MAJI decomposes the task into multiple specialized agents followed by editing and convergence steps, each run in sequence.

While not instantaneous, this latency remains acceptable in a human-in-the-loop interview setting, where brief pauses between questions are natural. We position MAJI as a near real-time assistant—optimized for insight and originality over immediacy—designed to support, not replace, the journalist's creative process. Future work will explore techniques such as model distillation, agent parallelization, and incremental reasoning to reduce latency.

Table 11: Average latency per question. Measured from the start of MAJI's pipeline to final output.

System	Avg. Latency (s)
LLM Baselines (Avg.)	1.42
MAJI V1	4.22
MAJI V2	16.59
MAJI V3	20.48

A.8 In-the-Field User Study

To assess MAJI's real-world applicability, we conducted a live deployment with a professional journalist during a 15-minute interview. The MAJI V2 system was accessed via a web-based dashboard on a MacBook Pro M2, positioned adjacent to the interview screen. It continuously updated suggestions based on transcribed utterances (via Whisper X), using GPT-4.1-mini with a context window of the last two speaker turns.

Over the course of the interview, the journalist asked 24 questions: 7 (29%) were adopted directly from MAJI's output, and 5 (21%) were minor variations. The remaining 12 were entirely original. Adopted questions were described as 'creative'—e.g., "Have you ever changed your reporting strategy based on your interviewee's mood?"—as opposed to clarifying prompts.

Despite MAJI's average 16 second generation latency, the journalist found the system non-disruptive. Two coping strategies helped: (1) high-quality suggestions remained relevant across multiple turns, and (2) the journalist could "buy time" by summarizing prior content while waiting for the next batch.

This study demonstrates that MAJI can be successfully integrated into real-time journalistic workflows. The journalist reported that MAJI enhanced creativity under deadline pressure. While this pilot involved a single professional, MAJI's architecture generalizes to other interactive formats. Ethical consent was obtained prior to deployment, and no interviewee data was retained.

A.9 Data Statement

Our study utilizes a combination of publicly available and proprietary datasets. The public data is drawn from the *NewsInterview* dataset (Lu et al., 2024), which consists of previously published interview transcripts. As such, it does not contain personally identifiable information beyond what was already made public by the original news organizations.

Our proprietary data consists of interview transcripts from a media tech company. As detailed in our Ethical Considerations, this data was used with explicit consent, and robust anonymization procedures were applied to protect the privacy of all individuals involved.

We acknowledge the ethical complexities of using real-world interview data. Some interviews may touch on sensitive topics, and we have handled this data with care. Furthermore, while the datasets we used are intended for research, we recognize that the copyright of the original material resides with the news organizations. Our use of this data is strictly for non-commercial research purposes to advance the understanding of computational tools in journalism.

A.10 Annotator and Participant Statement

The human evaluation and user study involved professional journalists who participated on a voluntary basis. The 30 journalists who participated in the qualitative survey (Appendix A.5) and the journalist who participated in the in-the-field user study (Appendix A.8) were colleagues from a media tech company. We are grateful for their time and expert feedback, which was essential for validating the practical applicability of our work. No monetary compensation was provided. All participants were informed about the research goals and how their feedback would be used.

A.11 Computational Resources

All experiments were run with OpenAI resources where a total of 150 dollars was spent.

B System Prompts

This section contains the core prompts used for the LLM baselines and the various MAJI agents. Each prompt is enclosed in a code block for clarity, with placeholders like `{placeholder}` representing dynamically populated data. Prompts are organized by system version for ease of reference.

B.1 LLM Baselines

Figure 1: LLM-Base Prompt

```
You are a professional interviewer. Based
    on the following information, please
    generate {num_questions} suitable next
    questions for the interview.

[Interviewee Information]
{persona_str}

[Interview Outline]
{outline_str}

[Conversation History]
{history}

Please output the list of questions in JSON
    array format, for example:
["Question 1", "Question 2", "Question 3"]
```

Figure 2: LLM-CoT Appended Instruction

```
First, think step-by-step about the
    interview's goal, the interviewee's
    personality, and the recent
    conversation flow. Consider what topics
    are yet to be covered and what previous
    points could be explored deeper. Based
    on this reasoning, then generate the
    questions.
```

Figure 3: LLM-ToT Appended Instruction

```
Explore multiple reasoning paths to decide
    on the best questions.
1. Path 1: Focus on deepening the last
    topic.
2. Path 2: Focus on transitioning to a new
    topic.
3. Path 3: Focus on the interviewee's
    emotional state.
Evaluate these paths and generate a final
    list of questions that synthesizes the
    best options.
```

Figure 4: LLM-RAG Appended Instruction

```
[Retrieved from long-term memory]
Here are some potentially relevant snippets
    from earlier in the conversation:
{retrieved_context}

Based on the conversation history AND the
    retrieved memories, generate the next
    questions.
```

B.2 MAJI V1 Agents

Figure 5: MAJI V1: DAgent Prompt Summary

```
You are the interview's thinking engine,
    responsible for divergent analysis.
    Your core tasks are:
 1. Match the current answer to the outline.
 2. Identify emotional expressions.
 3. Analyze logical connections.
 4. Identify important, uncovered areas in
     the outline.
 5. Generate exploratory follow-up
     questions.
 6. Extract key memory snippets.
You must follow strict matching criteria
    and output a valid JSON containing a
    `DivergentAnalysis` object. Follow-up
    questions should be natural, fluent,
    and avoid simply repeating the outline.
```

Figure 6: MAJI V1: CAgent Prompt Summary

```
You are the interview's strategy director.
    Based on the full divergent analysis,
    generate the single next question. Your
    key output must include the
    `next_question`, `reasoning` for your
    choice, the `exploration_strategy` used
    (from a predefined list), and scores
    for `novelty` and `depth`. You must
    strictly follow the JSON output format
    and ensure the question is natural and
    fluent.
```

B.3 MAJI V2 Agents

Figure 7: MAJI V2: BackgroundAgent Prompt

```
You are an AI assistant that maintains a
    dynamic background summary for an
    ongoing interview. Your task is to
    integrate the latest conversation turn
    into the existing background summary.
```

Figure 8: MAJI V2: KeywordsAgent Prompt

```
You are an AI assistant that extracts
    critical keywords from the latest
    conversation turn. Use the provided
    background summary to identify keywords
    that are not only salient to the
    current turn but also connect to the
    broader conversation context.
```

Figure 9: MAJI V2: OutlineMatcherAgent Prompt

```
You are a precise AI analyst. Your sole job
    is to match the user's latest response
    to a specific question in the provided
    interview outline. You must determine
    the best match and assess how well the
    response covers the question.
```

B.3.1 Divergent Agent Committee

All divergent agents share a common preamble, followed by their specific specialization instructions.

Figure 10: MAJI V2: Divergent Agent Common Preamble

```
You are a creative and insightful interview
    question generator. Your goal is to
    propose at least one, and up to three,
    thoughtful follow-up questions based on
    the provided context. Your output MUST
    be a valid JSON object. Do not simply
    repeat questions from the outline.
```

Figure 11: ChainOfThoughtDivergentAgent Specialization

```
Your Specialization: Logic and Causality
Focus on the 'why' and 'how'. Analyze the
    logical flow of the conversation. Ask
    questions that uncover motivations,
    processes, and consequences. Connect
    ideas that were mentioned but not
    explicitly linked. Do chain-of-thought
    reasoning for each question.
```

Figure 12: EmotionDivergentAgent Specialization

```
Your Specialization: Emotional Depth
Focus on the feelings and emotions behind
    the words. Ask questions that explore
    the interviewee's emotional state,
    values, and personal significance of
    their experiences. Listen for subtext
    and unspoken feelings.
```

Figure 13: OutlineDivergentAgent Specialization

```
Your Specialization: Structured Progression
Your goal is to ensure the interview covers
    all essential topics from the outline.
    Ask questions that bridge the current
    conversation to uncovered,
    high-priority, or logically adjacent
    topics in the outline. Your questions
    should be inspired by the outline but
    phrased naturally in the context of the
    conversation.
```

Figure 14: PersonaDivergentAgent Specialization

```
Your Specialization: Role-playing
Think from the interviewee's perspective.
    Based on their persona (background,
    personality, goals), what question
    would they find most engaging or
    relevant? Ask questions that resonate
    with their stated experiences and
    character.
```

Figure 15: NoveltyDivergentAgent Specialization

```
Your Specialization: Creative Surprise
Your goal is to introduce novel angles and
    break patterns. Ask questions that are
    unexpected but still relevant. Think
    about metaphors, hypothetical
    scenarios, or connections to broader
    themes that haven't been touched upon.
    Challenge assumptions.
```

Figure 16: MAJI V2: EditorAgent Prompt

```
You are an expert editor. Your task is to
    review a list of proposed interview
    questions from different AI agents.
    Your goal is to clean up this list by
    removing duplicates and combining very
    similar questions.
```

Figure 17: MAJI V2: ConvergentAgent Prompt

```
You are the Editor-in-Chief of this
    interview, responsible for selecting
    the single best question to ask next.
    You will be given a list of candidate
    questions from various specialist
    agents. Your decision should be guided
    by the user's stated preference for the
    interview's direction.
```

B.4 MAJI V3 Agents

Figure 18: MAJI V3: EditorInChiefAgent Prompt

```
You are the Editor-in-Chief of a dynamic
    interview system. Your role is to
    analyze the state of the conversation
    and devise a strategy for which *types*
    of questions to ask next. Based on the
    persona, summary, keywords, and outline
    coverage, generate a diverse and
    creative set of 2-4 divergent agent
    specifications. Each specification
    should include a unique, descriptive
    name and a clear set of instructions
    for that agent to follow.
```

B.5 Evaluation Prompts

This section contains the prompts used for evaluating the quality of generated questions, including both LLM-as-judge prompts and Prometheus evaluation rubrics.

B.5.1 LLM-as-Judge Prompts

Figure 19: QualitativeJudgeAgent Prompt

```
You are an expert conversational analyst.
    Your task is to evaluate a single
    proposed interview question based on
    the conversation's context. Provide
    scores from 0.0 to 1.0 for the
    following two subjective qualities:
1. Conversational Flow: Does the question
    feel like a natural, smooth
    continuation of the dialogue, or is it
    abrupt and jarring?
2. Elaboration: Does the question encourage
    the interviewee to provide a detailed,
    in-depth, and comprehensive answer,
    rather than a short or simple one?

Your output MUST be a single JSON object
    with the keys: `flow`, `elaboration`.
```

Figure 20: PersonaJudgeAgent Prompt

```
You are an expert profiler and interviewer.
    You will be given an interviewee's
    persona and a proposed question. Your
    task is to evaluate how well the
    question aligns with the interviewee's
    stated background, personality, and
    goals. A high score means the question
    would be engaging, relevant, and
    interesting *to this specific person*.
    A low score means it is too generic,
    irrelevant, or misaligned with their
    character.

Your output MUST be a single JSON object
    with the key: `alignment_score` (a
    float from 0.0 to 1.0).
```

Figure 21: CoherenceJudgeAgent Prompt

```
You are an expert in discourse analysis.
    You will be given the last question
    asked, the answer given, and a new
    proposed question. Your task is to
    evaluate the logical and thematic
    coherence of the new question as a
    follow-up. A high score means the
    question is a sensible, well-connected
    continuation of the dialogue. A low
    score means it feels abrupt, random,
    disconnected, or ignores the context of
    the previous answer.

Your output MUST be a single JSON object
    with the key: `coherence_score` (a
    float from 0.0 to 1.0).
```

Figure 22: InsightJudgeAgent Prompt

```
You are an expert conversation analyst.
    Your task is to categorize a proposed
    interview question based on the full
    context of the interview history.
    Analyze how the question relates to the
    entire dialogue, not just the last turn.

Categories:
- `Connecting`: The question links the
    current topic to a significantly
    earlier part of the conversation (more
    than 2-3 turns ago).
- `Challenging`: The question identifies
    and probes a potential contradiction,
    inconsistency, or assumption in the
    interviewee's statements.
- `Motivational`: The question explores the
    deep-seated 'why' behind an answer,
    focusing on core values, goals, or
    driving forces.
- `Hypothetical`: The question poses a
    creative 'what if' scenario to explore
    the interviewee's principles or
    thinking process.
- `SurfaceLevel`: A standard, logical
    follow-up that explores the immediate
    topic but lacks a deeper connection or
    creative angle.

Your output MUST be a single JSON object
    with the keys: `insight_category` and
    `reasoning`.
```

Figure 23: PlanEvaluatorAgent Prompt

```
You are an expert evaluator of AI agent
    systems. Your task is to assess the
    quality of a *plan* for generating
    interview questions, not the questions
    themselves. The plan consists of a list
    of specialist agents that will be
    created to handle the current
    situation. Evaluate the plan based on
    the conversational context.

1. Plan Relevance: How well does the chosen
    set of agents address the immediate
    needs of the conversation? (e.g., if
    the user is being emotional, is there
    an 'Emotion' agent planned?).
2. Plan Creativity: How creative is the
    plan? Does it propose novel specialists
    to find unique angles, or is it a
    generic, boilerplate plan?

Your output MUST be a single JSON object
    with the keys: `plan_relevance` and
    `plan_creativity`.
```

Figure 24: CategorizerAgent Prompt

```
You are an expert in conceptual analysis.
    You will be given a list of interview
    questions. Your task is to assign a
    single, concise conceptual category
    label to each question. For example,
    'Career Motivation', 'Work-Life
    Balance', 'Technical Skills'. You MUST
    return a list of strings, where each
    string is the category for the
    corresponding input question. The list
```

```
    must have the same number of items as
    the input list.
```

B.5.2 Prometheus Evaluation Rubrics

The following rubrics were used with the Prometheus 2 evaluation model to provide standardized, third-party assessment of question quality.

Figure 25: Context Relevance Rubric

```
Criteria: How well does the question
    logically follow from the interviewee's
    previous answer?

Score Descriptions:
1: Not at all relevant.
2: Slightly relevant.
3: Moderately relevant.
4: Relevant.
5: Highly relevant.
```

Figure 26: Insight Rubric

```
Criteria: Does the question probe deeper,
    encouraging novel reflection?

Score Descriptions:
1: Surface-level.
2: Asks for basic elaboration.
3: Encourages some reflection.
4: Prompts connection of ideas.
5: Deeply insightful.
```

Figure 27: Strategic Progression Rubric

```
Criteria: Does the question creatively
    bridge the current dialogue with the
    intended interview structure (outline),
    or does it just bluntly repeat an
    outline point?

Score Descriptions:
1: Completely ignores or contradicts the
    outline's direction.
2: Bluntly asks a question from the outline
    without connecting it to the
    conversation.
3: Loosely connects to an outline topic but
    the transition is awkward.
4: Smoothly transitions to an outline
    topic, clearly building on the last
    answer.
5: Artfully weaves an outline topic into
    the conversation, making the transition
    feel both natural and strategic.
```

Figure 28: Persona Alignment Rubric

```
Criteria: How well-suited is this question
    to the interviewee's specific
    background, expertise, and known
    interests as described in their
    persona? A good question is tailored to
    elicit a unique and insightful answer
    based on the interviewee's specific
    experiences.

Score Descriptions:
1: Generic question, irrelevant to the
    interviewee's specific persona.
2: Vaguely related to the interviewee's
    field, but not tailored to their
    specific role or accomplishments.
3: Asks about a topic relevant to the
    interviewee, but it's a standard
    question that doesn't probe their
    unique expertise.
4: The question is well-tailored, touching
    on specific aspects of the
    interviewee's known experience or
    expertise.
5: Excellent question that targets the core
    of the interviewee's unique expertise
    or perspective, making it highly likely
    to elicit a novel and insightful
    response.
```

Figure 29: Conversational Synthesis Rubric

```
Criteria: Does the question connect the
    interviewee's most recent answer with
    earlier parts of the conversation,
    weaving together themes, or does it
    treat each turn as an isolated event?

Score Descriptions:
1: Feels completely disconnected from the
    rest of the conversation history.
2: Vaguely references something said
    earlier, but the connection is weak.
3: Makes a simple, direct link to an
    immediately preceding turn.
4: Connects the current answer to a broader
    theme discussed earlier in the
    conversation.
5: Masterfully synthesizes multiple points
    from the conversation history to create
    a deeply contextualized and insightful
    question.
```

Figure 30: Perspective Diversity Rubric

```
Criteria: How diverse are these questions
    in their angle of approach and topic?
    Do they explore different facets of the
    previous answer, or are they all very
    similar to each other?

Score Descriptions:
1: All questions are essentially
    rephrasings of the same core idea.
2: Most questions are similar, with only
    minor variations in phrasing.
3: Some questions show different angles,
    but most are still on the same theme.
4: The questions explore a good variety of
    different topics and perspectives.
5: The questions are highly diverse, each
    approaching the conversation from a
    unique and creative angle.
```

Figure 31: Relative Comparison Rubric

```
Criteria: Which of the two proposed
    questions is a better, more insightful,
    and more natural follow-up to the
    conversation?

This rubric is used for pairwise
    comparisons between questions from
    different systems, with the judge
    selecting either response A, response
    B, or declaring a tie.
```