COCHAIN: BALANCING INSUFFICIENT AND EXCESSIVE COLLABORATION IN LLM AGENT WORKFLOWS

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Paper under double-blind review

ABSTRACT

Large Language Models (LLMs) have demonstrated impressive performance in executing complex reasoning tasks. Chain-of-thought effectively enhances reasoning capabilities by unlocking the potential of large models, while multi-agent systems provide more comprehensive solutions by integrating the collective intelligence of multiple agents. However, both approaches face significant limitations. Single-agent with chain-of-thought, due to the inherent complexity of designing cross-domain prompts, faces collaboration challenges. Meanwhile, multi-agent systems consume substantial tokens and inevitably dilute the primary problem, which is particularly problematic in business workflow tasks. To address these challenges, we propose **Cochain**, a collaboration prompting framework that effectively solves the business workflow collaboration problem by combining knowledge and prompts at a reduced cost. Specifically, we construct an integrated knowledge graph that incorporates knowledge from multiple stages. Furthermore, by maintaining and retrieving a prompts tree, we can obtain prompt information relevant to other stages of the business workflow. We perform extensive evaluations of Cochain across multiple datasets, demonstrating that Cochain outperforms all baselines in both prompt engineering and multi-agent LLMs. Additionally, expert evaluation results indicate that the use of a small model in combination with Cochain outperforms GPT-4. Our code is available at `https://anonymous.4open.science/r/Cochain-F871`.

1 INTRODUCTION

Large Language Models (LLMs) have achieved strong performance on language understanding and complex reasoning tasks (Touvron et al., 2023a; Bai et al., 2023; GLM et al., 2024; Bi et al., 2024). Much of this progress is unlocked at inference time. Prompting techniques such as Chain-of-Thought encourage step-by-step reasoning and often improve depth of reasoning (Wei et al., 2022; Besta et al., 2024). In parallel, multi-agent frameworks extend a single model into a team of specialized roles and interaction protocols, aiming to provide broader coverage across domains such as healthcare, education, law, and finance (Tang et al., 2024; Dan et al., 2023; Cui et al., 2024; Yang et al., 2023). However, a practical question remains: How much collaboration is actually needed for high-quality decision making?

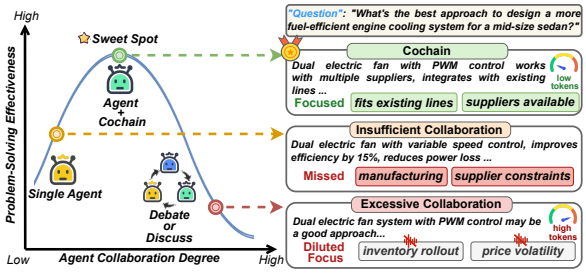

Figure 1: Collaboration has a Goldilocks region. Insufficient Collaboration overlooks cross-stage constraints and dependencies, whereas Excessive Collaboration injects peripheral details that dilute the core decision and increase token cost. Cochain enforces stage constraints while keeping the solution focused. In a car manufacturing query, a single agent misses manufacturing and supplier constraints, while excessive discussion drifts to inventory rollout and price volatility.

This question is especially salient in business workflow tasks. We define a *Business Workflow* as a complex process consisting of many interconnected stages. The stages are specialized, and they strongly depend on each other. A decision made in one stage requires more than local

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expertise. It must anticipate and incorporate knowledge and constraints from other stages. For example, in an automotive manufacturing workflow, design and production choices must align with what the supply chain can actually provide. In this setting, we observe two opposite failure modes (Figure 1). **Insufficient Collaboration** arises when the overall system does not effectively integrate downstream constraints into the decision process, so solutions may look locally reasonable but violate workflow level requirements (Sahoo et al., 2024). **Excessive Collaboration** arises when many agents participate directly and simultaneously in each decision, making interaction expensive and unfocused, so non critical information overwhelms the main issue and the system may prefer consensus-like answers over accurate ones (Du et al., 2024; Zhang et al., 2024b). Existing research on multi-agent systems primarily focuses on maximizing collaboration, extensively exploring how multi-agent systems improve decision quality (Zhang et al., 2025b), make safe decisions (Piatti et al., 2024), and solve complex problems (Li et al., 2025). In contrast, the negative effects of excessive collaboration have received insufficient attention, particularly in multi-stage business workflows (Lei et al., 2025). **To our best knowledge, no prior work has systematically analyzed and defined this *Excessive Collaboration* phenomenon in workflow settings, nor proposed targeted solutions to mitigate it.** We therefore seek effective collaboration that is stage aware and focused, without paying the full cost of direct multi-agent chatting.

To this end, we propose **Cochain**, a chain-of-collaboration prompting framework for business workflows. Cochain replaces token-intensive direct interaction with retrieval of reusable collaboration artifacts distilled from agents and data (Figure 2). It constructs a **collaborative knowledge graph** that fuses explicit knowledge from the original datasets with tacit knowledge elicited from specialized agents via counterfactual questioning. To mitigate the influence of irrelevant knowledge (Zhou et al., 2024), retrieved evidence is organized into compact **causal chains** that connect stage-specific information through shared bridge entities, supporting cross-stage reasoning while filtering noise. Cochain also builds a **prompts tree** that distills reusable, solution-oriented prompts from agent responses and organizes them across workflow stages. Inspired by how the human brain integrates fragmented knowledge into coherent thought (Courellis et al., 2024), the prompt tree is designed to provide structured cross-stage guidance: querying the tree yields a **prompt chain** tailored to the input, guiding the backbone model through stage-specific reasoning in a consistent order. At inference time, Cochain retrieves stage-relevant knowledge, a causal chain from the knowledge graph, and a prompt chain from the prompt tree, then composes them into a structured prompt for the backbone LLM. This produces workflow-aware yet focused answers, balancing insufficient collaboration and excessive collaboration. The main contributions are summarized as follows:

- **Effective collaboration.** We identify two opposite collaboration failures in business workflow tasks, insufficient collaboration that misses cross-stage constraints and excessive collaboration that dilutes the core decision with excessive interaction.
- **Cochain framework.** We propose Cochain, which enables stage-aware collaboration via reusable artifacts rather than token-heavy interactions. Cochain combines a collaborative knowledge graph with causal-chain retrieval and a prompts tree that composes prompt chains for coherent multi-stage reasoning.
- **Empirical evidence and expert support.** Experiments across benchmarks and backbones show Cochain improves quality with efficient inference. Expert evaluation suggests a smaller model with Cochain can outperform a larger one. We will release our collaborative knowledge graph to support future research.

2 Related Work

2.1 Knowledge Graph Augmented LLMs

LLM reasoning capabilities are critical for high-quality responses (Jain et al., 2024). Knowledge graphs, with their structured, explicit, and interpretable nature (Zhou et al., 2025), provide clear representations and transparent reasoning paths, guiding LLMs toward deeper reasoning and mitigating limitations (Wang et al., 2024). For domain-specific LLMs, knowledge graphs enable continuous knowledge updates to accommodate evolving information (Lavrinovics et al., 2025). Applications include MindMap (Wen et al., 2024) in medicine and ChatLAW (Cui et al., 2024) in law. Business workflows pose an additional challenge of multi-stage, cross-domain knowledge fusion, where

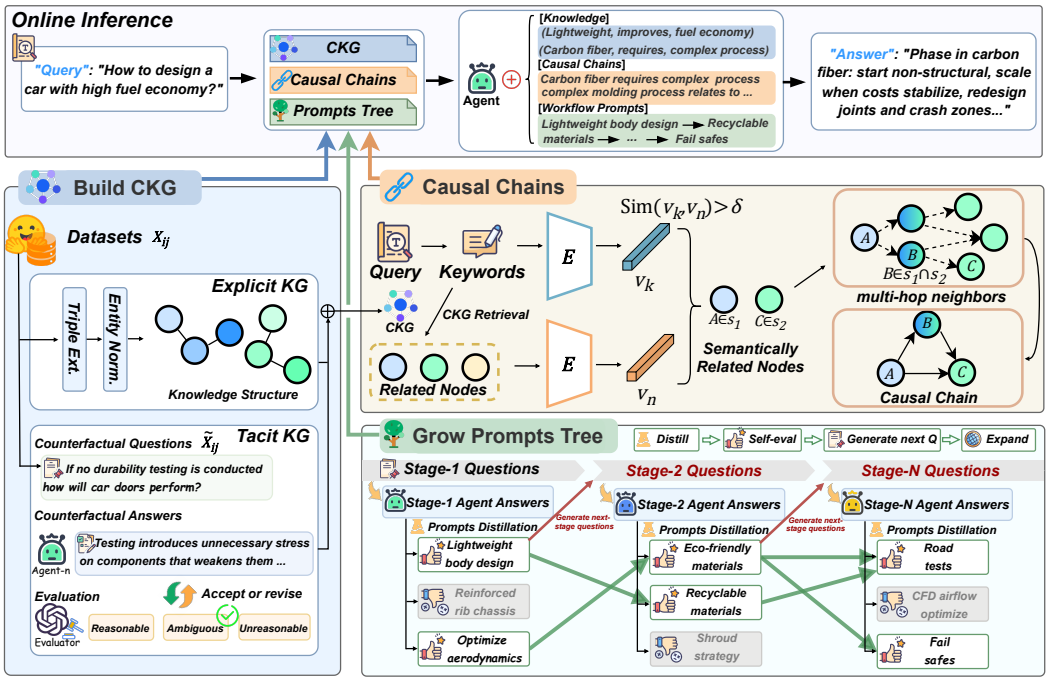


Figure 2: Overview of Cochain. Offline, we construct a Collaborative Knowledge Graph (CKG) by combining explicit triples from workflow data with tacit triples elicited via counterfactual querying and iterative verification, and build a Prompts Tree through cross-stage prompt distillation. Online, Cochain retrieves stage-relevant knowledge from the CKG, composes causal chains, and leverages the Prompts Tree to propagate necessary constraints across stages, mitigating insufficient collaboration and excessive collaboration.

irrelevant knowledge can easily overwhelm the core decision and degrade performance (Ouyang et al., 2022). To address this, Cochain organizes retrieved evidence into causal chains, improving cross-stage understanding while filtering noise.

2.2 Prompt Engineering

Prompt engineering guides LLMs to maximize their potential via designed prompts (Sahoo et al., 2024). It enables model adaptation to new tasks through in-context learning and instruction following (Brown et al., 2020; Li et al., 2023). Well-designed prompts are shown to enhance performance, particularly on complex tasks (Wei et al., 2022; Wang et al., 2023; Yao et al., 2023). CoT (Wei et al., 2022) enables models to generate intermediate reasoning steps via simple prompts. ToT (Yao et al., 2024) explores coherent text units as intermediate problem-solving steps. CPO (Zhang et al., 2024a) leverages non-optimal reasoning paths from tree search to speed up inference. However, these methods are typically designed for a single decision context and do not explicitly maintain constraint awareness across stages or support cross-domain coordination in business workflows. Cochain complements this line by distilling cross-stage prompts from agent responses and organizing them into prompts tree for retrieval.

2.3 Collaboration of LLM Agents

Many studies in LLM research solve problems through multi-agent collaboration (Du et al., 2024; Zhao et al., 2024). Common paradigms include discussion (Tang et al., 2024) and debate (Du et al., 2024) to enhance reasoning, hierarchical structures with specialized roles (Zhang et al., 2025a), and sequential or tree-structured architectures (Zhang et al., 2024b; Zhao et al., 2024). These have proven effective in domains like medicine (Tang et al., 2024), long-text processing (Zhang et al., 2024b; Zhao et al., 2024), social simulation (Wei et al., 2024), and code intelligence (Huang et al., 2023). Most

Table 1: Performance comparison of different model backbones and multi-agent baselines across three business domains. We report the mean and standard error (SE) over five experiments. BERTScore F1 is abbreviated as BS-F. We highlight the best and second-best results.

Backbone	Baseline	Automotive			Pharmaceutical			E-commerce		
		BS-F	GLEU	ROUGE-L	BS-F	GLEU	ROUGE-L	BS-F	GLEU	ROUGE-L
openPangu-1B	PMC	72.28$_{\pm 0.08}$	12.62$_{\pm 0.10}$	22.89$_{\pm 0.14}$	75.67$_{\pm 0.31}$	20.66$_{\pm 0.44}$	29.74$_{\pm 0.26}$	73.96$_{\pm 0.19}$	11.77$_{\pm 0.40}$	19.94$_{\pm 0.43}$
	MedAgents	69.95$_{\pm 0.22}$	10.40$_{\pm 0.31}$	20.22$_{\pm 0.25}$	72.82$_{\pm 0.17}$	17.72$_{\pm 0.31}$	27.12$_{\pm 0.37}$	74.63$_{\pm 0.16}$	21.22$_{\pm 0.34}$	28.99$_{\pm 0.44}$
	Debate(short)	71.36$_{\pm 0.11}$	10.72$_{\pm 0.23}$	21.45$_{\pm 0.17}$	75.74$_{\pm 0.41}$	21.87$_{\pm 0.21}$	30.11$_{\pm 0.27}$	75.73$_{\pm 0.33}$	28.05$_{\pm 0.28}$	31.05$_{\pm 0.21}$
	Debate(long)	70.59$_{\pm 0.20}$	10.21$_{\pm 0.27}$	20.85$_{\pm 0.19}$	73.77$_{\pm 0.37}$	18.13$_{\pm 0.23}$	27.61$_{\pm 0.15}$	75.38$_{\pm 0.44}$	16.98$_{\pm 0.34}$	25.27$_{\pm 0.29}$
	CoA	69.61$_{\pm 0.31}$	8.54$_{\pm 0.47}$	18.60$_{\pm 0.29}$	73.82$_{\pm 0.33}$	18.79$_{\pm 0.21}$	28.00$_{\pm 0.33}$	74.75$_{\pm 0.27}$	17.32$_{\pm 0.28}$	24.10$_{\pm 0.31}$
	Cochain	74.35$_{\pm 0.05}$	15.99$_{\pm 0.07}$	26.01$_{\pm 0.03}$	76.40$_{\pm 0.10}$	22.10$_{\pm 0.08}$	30.71$_{\pm 0.13}$	77.06$_{\pm 0.04}$	23.37$_{\pm 0.14}$	31.64$_{\pm 0.11}$
openPangu-7B	PMC	71.41$_{\pm 0.13}$	11.06$_{\pm 0.17}$	21.01$_{\pm 0.21}$	70.65$_{\pm 0.41}$	15.77$_{\pm 0.39}$	23.42$_{\pm 0.30}$	71.77$_{\pm 0.23}$	19.55$_{\pm 0.39}$	25.97$_{\pm 0.30}$
	MedAgents	70.00$_{\pm 0.24}$	10.63$_{\pm 0.28}$	20.26$_{\pm 0.30}$	73.06$_{\pm 0.26}$	18.20$_{\pm 0.21}$	25.35$_{\pm 0.52}$	71.69$_{\pm 0.18}$	19.45$_{\pm 0.36}$	22.89$_{\pm 0.53}$
	Debate(short)	70.11$_{\pm 0.18}$	10.00$_{\pm 0.21}$	19.78$_{\pm 0.34}$	70.73$_{\pm 0.35}$	12.34$_{\pm 0.26}$	20.77$_{\pm 0.35}$	68.56$_{\pm 0.29}$	18.15$_{\pm 0.23}$	19.62$_{\pm 0.32}$
	Debate(long)	69.90$_{\pm 0.18}$	9.43$_{\pm 0.21}$	19.56$_{\pm 0.29}$	70.67$_{\pm 0.41}$	13.83$_{\pm 0.22}$	20.73$_{\pm 0.31}$	68.42$_{\pm 0.27}$	17.43$_{\pm 0.36}$	19.44$_{\pm 0.27}$
	CoA	68.25$_{\pm 0.34}$	7.95$_{\pm 0.35}$	17.32$_{\pm 0.43}$	70.21$_{\pm 0.40}$	14.53$_{\pm 0.26}$	22.98$_{\pm 0.24}$	70.03$_{\pm 0.25}$	19.09$_{\pm 0.29}$	22.80$_{\pm 0.23}$
	Cochain	74.17$_{\pm 0.08}$	15.49$_{\pm 0.05}$	25.62$_{\pm 0.09}$	70.93$_{\pm 0.09}$	19.40$_{\pm 0.05}$	25.21$_{\pm 0.11}$	73.83$_{\pm 0.07}$	19.60$_{\pm 0.25}$	23.00$_{\pm 0.11}$
Qwen2-7B	PMC	65.86$_{\pm 0.03}$	13.23$_{\pm 0.08}$	18.35$_{\pm 0.07}$	66.97$_{\pm 0.79}$	16.25$_{\pm 0.58}$	24.75$_{\pm 0.62}$	71.02$_{\pm 0.17}$	24.18$_{\pm 0.37}$	29.93$_{\pm 0.45}$
	MedAgents	65.16$_{\pm 0.25}$	12.37$_{\pm 0.17}$	18.33$_{\pm 0.18}$	65.84$_{\pm 0.15}$	10.68$_{\pm 0.36}$	20.83$_{\pm 0.50}$	69.45$_{\pm 0.19}$	17.42$_{\pm 0.17}$	33.38$_{\pm 0.18}$
	Debate(short)	65.30$_{\pm 0.26}$	12.42$_{\pm 0.37}$	17.63$_{\pm 0.23}$	70.62$_{\pm 0.41}$	16.04$_{\pm 0.35}$	24.12$_{\pm 0.49}$	73.03$_{\pm 0.43}$	20.89$_{\pm 0.32}$	28.27$_{\pm 0.29}$
	Debate(long)	65.61$_{\pm 0.27}$	12.85$_{\pm 0.47}$	18.28$_{\pm 0.13}$	60.57$_{\pm 0.30}$	10.28$_{\pm 0.39}$	11.21$_{\pm 0.52}$	72.41$_{\pm 0.60}$	20.82$_{\pm 0.59}$	28.46$_{\pm 0.53}$
	CoA	70.70$_{\pm 0.53}$	21.51$_{\pm 0.41}$	22.65$_{\pm 0.68}$	76.98$_{\pm 0.44}$	30.45$_{\pm 0.42}$	34.00$_{\pm 0.17}$	79.24$_{\pm 0.18}$	38.60$_{\pm 0.35}$	39.14$_{\pm 0.62}$
	Cochain	75.05$_{\pm 0.17}$	27.66$_{\pm 0.26}$	28.43$_{\pm 0.23}$	78.50$_{\pm 0.04}$	34.48$_{\pm 0.28}$	35.23$_{\pm 0.17}$	80.22$_{\pm 0.16}$	37.83$_{\pm 0.38}$	40.84$_{\pm 0.41}$
DeepSeek-R1-7B	PMC	65.94$_{\pm 0.13}$	10.75$_{\pm 0.23}$	15.78$_{\pm 0.13}$	68.06$_{\pm 0.27}$	22.51$_{\pm 0.29}$	28.07$_{\pm 0.20}$	66.66$_{\pm 0.43}$	15.80$_{\pm 0.39}$	23.62$_{\pm 0.30}$
	MedAgents	65.58$_{\pm 0.60}$	8.03$_{\pm 0.55}$	14.08$_{\pm 0.59}$	70.35$_{\pm 0.14}$	24.47$_{\pm 0.19}$	30.90$_{\pm 0.08}$	66.98$_{\pm 0.49}$	13.67$_{\pm 0.49}$	20.31$_{\pm 0.60}$
	Debate(short)	65.93$_{\pm 0.23}$	11.41$_{\pm 0.44}$	17.33$_{\pm 0.52}$	71.46$_{\pm 0.31}$	27.13$_{\pm 0.27}$	30.34$_{\pm 0.44}$	70.71$_{\pm 0.29}$	23.01$_{\pm 0.22}$	27.02$_{\pm 0.39}$
	Debate(long)	66.06$_{\pm 0.67}$	12.13$_{\pm 0.49}$	17.70$_{\pm 0.26}$	71.54$_{\pm 0.42}$	27.34$_{\pm 0.39}$	30.04$_{\pm 0.39}$	70.48$_{\pm 0.39}$	23.07$_{\pm 0.10}$	27.00$_{\pm 0.44}$
	CoA	70.83$_{\pm 0.29}$	13.27$_{\pm 0.58}$	17.51$_{\pm 0.58}$	77.06$_{\pm 0.15}$	38.18$_{\pm 0.49}$	35.53$_{\pm 0.23}$	80.43$_{\pm 0.32}$	43.80$_{\pm 0.39}$	42.03$_{\pm 0.43}$
	Cochain	73.20$_{\pm 0.02}$	21.45$_{\pm 0.17}$	23.89$_{\pm 0.13}$	79.11$_{\pm 0.09}$	38.27$_{\pm 0.17}$	37.21$_{\pm 0.21}$	82.68$_{\pm 0.05}$	50.19$_{\pm 0.13}$	47.07$_{\pm 0.13}$
Claude-3.5-haiku	PMC	64.06$_{\pm 0.04}$	9.73$_{\pm 0.56}$	10.12$_{\pm 0.31}$	66.18$_{\pm 0.16}$	13.04$_{\pm 0.36}$	13.91$_{\pm 0.18}$	66.85$_{\pm 0.07}$	15.98$_{\pm 0.60}$	15.88$_{\pm 0.21}$
	MedAgents	64.38$_{\pm 0.10}$	10.77$_{\pm 0.56}$	11.02$_{\pm 0.14}$	66.01$_{\pm 0.17}$	14.60$_{\pm 0.30}$	14.66$_{\pm 0.29}$	68.00$_{\pm 0.13}$	17.58$_{\pm 0.31}$	16.51$_{\pm 0.14}$
	Debate(short)	64.36$_{\pm 0.17}$	11.21$_{\pm 0.39}$	13.72$_{\pm 0.33}$	69.11$_{\pm 0.11}$	14.53$_{\pm 0.26}$	16.03$_{\pm 0.28}$	68.41$_{\pm 0.43}$	19.97$_{\pm 0.32}$	18.37$_{\pm 0.31}$
	Debate(long)	65.13$_{\pm 0.08}$	11.79$_{\pm 0.49}$	12.13$_{\pm 0.39}$	67.68$_{\pm 0.10}$	15.94$_{\pm 0.31}$	15.13$_{\pm 0.32}$	67.49$_{\pm 0.67}$	17.23$_{\pm 0.42}$	18.98$_{\pm 0.56}$
	CoA	63.78$_{\pm 0.26}$	9.23$_{\pm 0.29}$	10.28$_{\pm 0.20}$	66.00$_{\pm 0.39}$	13.33$_{\pm 0.22}$	14.25$_{\pm 0.36}$	67.03$_{\pm 0.35}$	15.02$_{\pm 0.33}$	15.12$_{\pm 0.35}$
	Cochain	69.66$_{\pm 0.03}$	18.62$_{\pm 0.06}$	16.83$_{\pm 0.24}$	72.83$_{\pm 0.06}$	23.47$_{\pm 0.13}$	19.25$_{\pm 0.22}$	71.56$_{\pm 0.12}$	20.11$_{\pm 0.13}$	20.65$_{\pm 0.17}$

existing systems rely on richer interaction and repeated message exchanges, which increases token cost and can dilute the core decision in multi-stage workflows when peripheral opinions accumulate. Cochain instead uses reusable collaboration artifacts to deliver focused, stage-aware collaboration while keeping inference lightweight. To our best knowledge, no prior work has systematically defined *Excessive Collaboration* in this setting or proposed a targeted mitigation mechanism.

3 METHOD

3.1 COLLABORATIVE KNOWLEDGE GRAPH

Building a collaborative knowledge graph requires abundant stage-specific knowledge. We obtain it from the training sets of the workflow datasets, denoted as $D_i = \{(X_{ij}, Y_{ij})\}_{j=1}^{n_i}$, where $i \in \{1, \ldots, N\}$ indexes workflow stages, N is the number of stages, and $j \in \{1, \ldots, n_i\}$ indexes the n_i training instances in stage i. Here $X_{ij} \in X_i$ is the input and $Y_{ij} \in Y_i$ is the corresponding output. After data cleaning and triplet extraction, we construct an explicit knowledge graph $\mathcal{KG}_{\text{explicit}}$:

$$\mathcal{KG}_{\text{explicit}} = \bigcup_{i=1}^{N} \bigcup_{j=1}^{n_i} \text{ExtractTriples}(X_{ij}, Y_{ij}) \tag{1}$$

Business workflows also contain *tacit* knowledge that is rarely stated in the original datasets, such as feasibility constraints, implementation caveats, and stage-specific heuristics. Since such considerations are not explicitly available, we elicit tacit workflow knowledge from the agent's responses by probing the agent under counterfactual perturbations and attributing response variations to unobserved internal considerations.

For each sample (X_{ij}, Y_{ij}), we generate a counterfactual input $\tilde{X}_{ij}$ by editing X_{ij} to perturb one salient condition while preserving intent, using templates for causal, adversarial, substitution, extreme, and backward-causal variants:

$$\tilde{X}_{ij} = \text{GenerateCounterfactual}(X_{ij}) \tag{2}$$

In our setting, a vertical domain agent is the stage-specialized LLM assigned to stage i (fine-tuned on stage-i data for open-source backbones). We query this agent with $\tilde{X}_{ij}$ to obtain the counterfactual output $\tilde{Y}_{ij}$. To capture the unobserved considerations that shape how the agent resolves $\tilde{X}_{ij}$, we introduce a latent variable θ_{ij} and an intermediate latent state h_{ij} influenced by θ_{ij}, where $h_{ij} \mid \theta_{ij} \sim P(h_{ij} \mid \theta_{ij})$, and $\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij} \sim P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij})$. The resulting generation process can be written as:

$$P(\tilde{Y}_{ij} \mid \tilde{X}_{ij}) = \int_{\Theta} P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij}) \cdot P(h_{ij} \mid \theta_{ij})\, P(\theta_{ij} \mid \tilde{X}_{ij})\, d\theta_{ij} \tag{3}$$

Here, $P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij})$ is the likelihood of generating the counterfactual output given h_{ij} and $\tilde{X}_{ij}$, $P(h_{ij} \mid \theta_{ij})$ describes how tacit considerations shape the latent state, and $P(\theta_{ij} \mid \tilde{X}_{ij})$ is a prior over tacit considerations conditioned on the counterfactual input.

To improve reliability, each counterfactual answer is evaluated by a general-purpose LLM and assigned one of three labels: reasonable, ambiguous, or unreasonable. The evaluator provides feedback and revision suggestions, which the vertical agent uses to regenerate a response. This loop repeats until a reasonable answer is obtained. During knowledge distillation, we apply causal enhancement by emphasizing causal cues such as "depends on", "relies on", and "applies to", which helps preserve cross-stage dependency signals. Using the counterfactual input-output pairs $(\tilde{X}_{ij}, \tilde{Y}_{ij})$ produced by the refinement loop, we extract tacit triples and build a tacit knowledge graph $\mathcal{KG}_{\text{tacit}}$:

$$\mathcal{KG}_{\text{tacit}} = \bigcup_{i=1}^{N} \bigcup_{j=1}^{n_i} \text{ExtractTriples}(\tilde{X}_{ij}, \tilde{Y}_{ij}, \theta_{ij}) \tag{4}$$

Finally, we integrate explicit and tacit knowledge to form the collaborative knowledge graph $\mathcal{KG}$, which captures both stage-specific knowledge and inter-stage connectivity:

$$\mathcal{CKG} = \mathcal{KG}_{\text{explicit}} \cup \mathcal{KG}_{\text{tacit}} \tag{5}$$

3.2 Causal Chain

To help the agent organize cross-stage dependencies instead of merely listing retrieved facts, we introduce a causal chain mechanism. Given a user request, we decompose it and extract keywords, which are then used to retrieve relevant nodes from the collaborative knowledge graph.

Following Figure 2, we use a pre-trained text encoder (Reimers & Gurevych, 2019) to embed each keyword and candidate knowledge node. For the embedding v_k of keyword k and the embedding v_n of node n, we compute cosine similarity:

$$\text{Sim}(v_k, v_n) = \frac{v_k \cdot v_n}{\|v_k\| \|v_n\|} \tag{6}$$

With a similarity threshold δ, we select nodes that are semantically related to the query. For each selected node, we expand one-hop neighbors to introduce closely associated evidence and form a local triple-based structure. To connect knowledge across workflow stages, we further perform multi-hop exploration through *bridge entities*. Let the workflow stages be $\mathcal{S} = \{s_1, s_2, s_3, \dots\}$. For a high-similarity node A belonging to stage s_1, we expand a neighbor B that appears in both s_1 and some other stage s_i with $i \neq 1$. We then use B as a bridge to reach a node C in stage s_i, forming a cross-stage causal chain:

$$\text{CausalChain}(A, C) = A \xrightarrow{B} C \tag{7}$$

The causal chain provides a compact, stage-connected context that highlights how constraints and decisions propagate across stages, improving coherence and feasibility in the final response.

3.3 Prompts Tree

In business workflow tasks, effective collaboration requires stage-specific reasoning to be carried forward consistently and reusable across stages. We propose a prompt distillation procedure that

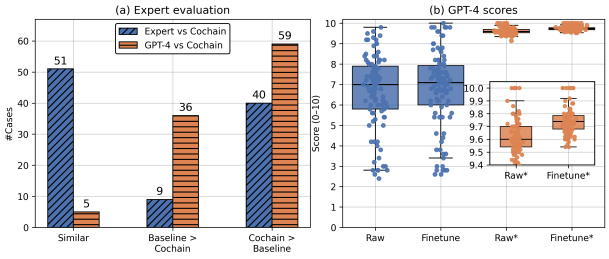


Figure 3: Expert evaluation and GPT-4 scoring results. Panel (a) compares Qwen2-7B with Cochain against GPT-4 and expert references (100 cases). In panel (b), the asterisk indicates augmentation with Cochain.

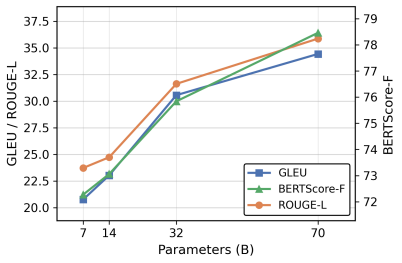


Figure 4: Comparative analysis of metrics scaling with increasing model size from DeepSeek-R1 7B to 70B.

offline constructs a **Prompts Tree**, which stores solution-oriented prompts and explicitly encodes cross-stage dependencies. We model the Prompts Tree as a rooted tree $T = (V, E)$. Each node $v \in V$ has a stage label $s(v) \in \mathcal{S}$, a distilled prompt $p(v)$, and supporting evidence, i.e., the Q&A used for distillation. Each directed edge $(u \to v) \in E$ denotes a dependency where upstream prompt $p(u)$ induces a downstream question template, whose answer leads to prompt $p(v)$. Querying T returns a **prompt chain** along a root-to-leaf path, providing structured cross-stage guidance during inference.

Tree construction. Starting from a seed Q&A at Stage 1, the Stage 1 agent distills candidate prompts that are solution-oriented and constraint-aware, emphasizing actionable decisions, feasibility conditions, and implementation requirements. These prompts are self-evaluated for utility and executability, and the top m are retained. For each retained prompt, we generate a downstream question template asking how to implement, validate, or satisfy it in the next stage. The next-stage agent answers these questions, producing new Q&A pairs for the next round of prompt distillation. This loop repeats across stages, allowing upstream prompts to branch into multiple downstream realizations.

Node and edge semantics. The user need is the root node, and Stage 1 prompts are its children. For a node u at stage s_k, each outgoing edge corresponds to a generated question template $q_{u\to}$ for stage s_{k+1}. The resulting answer yields a child node v at stage s_{k+1} with prompt $p(v)$. Thus, each child prompt is conditioned on satisfying or operationalizing its parent under downstream constraints, explicitly recording cross-stage dependencies.

Retrieval and usage. Inspired by how the human brain integrates fragmented knowledge into coherent thought (Courellis et al., 2024), the Prompts Tree organizes fragmented stage-specific guidance into an ordered chain. At inference, we retrieve a prompt chain $\pi = (v_0 \to v_1 \to \cdots \to v_L)$ that best matches the input query, and use the prompts $\{p(v_\ell)\}_{\ell=0}^{L}$ as structured guidance for the backbone LLM to reason through workflow stages in order.

4 Experiments

4.1 Experimental Setup

Datasets. We evaluate Cochain on two benchmarks across four datasets: Auto-SLURP (Shen & Shen, 2025), which assesses end-to-end multi-stage workflows, and MSCoRe (Lei et al., 2025), which focuses on multi-stage reasoning and collaboration. The automotive workflow test set is reviewed and refined by domain experts from a major automobile manufacturer to ensure practical industry relevance.

Metrics. We report BERTScore (Zhang et al., 2019), GLEU (Wu et al., 2016), and ROUGE-L (Lin, 2004) to measure semantic similarity and generation quality between model outputs and reference answers.

Table 2: Result of ablation study. We highlight the largest and second-largest drops from removing each component.

Backbone	Method	Automotive			Pharmaceutical			E-commerce		
		BS-F	GLEU	ROUGE-L	BS-F	GLEU	ROUGE-L	BS-F	GLEU	ROUGE-L
Qwen2-7B	Cochain	75.39	28.17	28.87	78.48	33.98	35.03	79.91	37.08	40.06
	w/o $\mathcal{CKG}$	75.21	27.81	28.74	76.34	25.92	28.09	76.72	32.40	32.74
	w/o Causal Chain	75.20	27.55	28.42	76.20	25.38	27.76	76.86	33.30	32.93
	w/o Prompts Tree	73.08	22.45	24.56	76.19	26.84	28.91	76.59	31.83	32.38
DeepSeek-R1-7B	Cochain	73.19	21.73	24.01	78.97	37.94	36.75	82.68	50.30	47.24
	w/o $\mathcal{CKG}$	72.41	19.71	22.63	78.22	37.33	36.40	77.36	36.54	35.85
	w/o Causal Chain	72.67	19.96	22.86	78.41	37.36	36.74	77.60	36.30	35.74
	w/o Prompts Tree	72.27	16.54	20.60	76.96	37.98	35.61	79.02	41.03	38.84
Claude-3.5-haiku	Cochain	69.61	18.73	17.30	72.87	23.59	19.67	71.36	20.15	20.78
	w/o $\mathcal{CKG}$	68.98	16.63	16.31	70.93	16.42	18.45	71.13	18.85	20.22
	w/o Causal Chain	69.33	17.31	16.65	71.33	17.43	18.78	71.23	18.89	20.45
	w/o Prompts Tree	65.79	12.84	13.71	70.85	16.24	18.31	69.76	15.55	18.59

Table 3: Accuracy comparison on Auto-SLURP.

Baseline	Backbone	
	DeepSeek-V3.1	Claude-3.5-haiku
PMC	0.12	0.29
MedAgents	0.07	0.26
Debate	0.32	0.31
CoA	0.27	0.37
Cochain	**0.33**	**0.38**

LLMs. We use 17 backbone LLMs, spanning proprietary and open-source models. We compare reasoning-capable models (e.g., DeepSeek-R1-7B (DeepSeek-AI, 2025)) with standard models (e.g., openPangu-7B (Chen et al., 2025), Qwen2-7B (qwe, 2024)). We further study identical versus mixed backbones across stages (Llama2-7B (Touvron et al., 2023b), GLM4-9B, Qwen2-7B, DeepSeek-7B) for specialization. For open-source backbones, we fine-tune the stage-k agent only on the stage-k training split of MSCoRe, excluding validation/test instances. Proprietary models include GPT-3.5-turbo, GPT-4o (Achiam et al., 2023), DeepSeek-V3.1 (DeepSeek-AI, 2024), and Claude-3.5-haiku.

Baselines. Our baselines cover predominant multi-agent collaboration methods. Specifically, PMC (Zhang et al., 2025a) uses hierarchical planning for multi-agent collaboration. MedAgents (Tang et al., 2024) supports collaborative decision-making through discussion and voting. Debate (Du et al., 2024) enables collaboration via argumentative discourse, while CoA (Zhang et al., 2024b) adopts chain-based collaboration. We also compare single-agent prompt engineering methods, including CoT (Wei et al., 2022) and ToT (Yao et al., 2024).

4.2 Result

Overall Results. Table 1 summarizes performance across three business domains and five backbones. The results support our central claim that effective workflow collaboration requires balancing *Insufficient* and *Excessive* Collaboration. Compared with interaction-heavy multi-agent baselines, which often cause excessive collaboration and diluted decisions, Cochain consistently achieves higher quality across domains. It also improves substantially on small backbones, suggesting that reusable stage-aware artifacts can mitigate insufficient collaboration without relying solely on stronger models.

Benchmark Transfer on Auto-SLURP. Table 3 confirms Cochain's advantage on an end-to-end workflow benchmark. Cochain achieves the highest accuracy with both DeepSeek-V3.1 and Claude-3.5-haiku, reaching 0.33 and 0.38, respectively. This supports that Cochain generalizes beyond MSCoRe-style text similarity metrics and remains effective across workflow stages.

Table 4: The performance of GPT-3.5-turbo and GPT-4o when using CoT, ToT, and Cochain.

Backbone	Method	BS-F	GLEU	ROUGE-L
GPT-3.5-turbo	+ IO	72.84$_{\pm 0.07}$	15.09$_{\pm 0.17}$	21.98$_{\pm 0.23}$
	+ CoT	71.61$_{\pm 0.17}$	11.15$_{\pm 0.17}$	17.92$_{\pm 0.16}$
	+ ToT	66.69$_{\pm 0.05}$	10.08$_{\pm 0.04}$	17.74$_{\pm 0.09}$
	+ Cochain	**76.94**$_{\pm 0.03}$	**28.92**$_{\pm 0.12}$	**30.65**$_{\pm 0.09}$
GPT-4o	+ IO	71.92$_{\pm 0.08}$	23.05$_{\pm 0.17}$	23.79$_{\pm 0.17}$
	+ CoT	72.57$_{\pm 0.15}$	23.76$_{\pm 0.14}$	24.15$_{\pm 0.28}$
	+ ToT	66.23$_{\pm 0.17}$	12.51$_{\pm 0.14}$	17.52$_{\pm 0.19}$
	+ Cochain	**74.46**$_{\pm 0.07}$	**25.16**$_{\pm 0.25}$	**25.07**$_{\pm 0.14}$

Table 5: Effect of skip stages on evaluation metrics.

Skip	Stage	BS-F	GLEU	ROUGE-L
zero	/	75.39	28.17	28.87
one	$S_1 \rightarrow S_3 \rightarrow S_5$	74.00	24.66	25.18
	$S_2 \rightarrow S_4$	74.52	25.57	26.18
	$S_3 \rightarrow S_5$	74.18	25.45	25.95
two	$S_1 \rightarrow S_3$	74.27	25.26	25.74
	$S_2 \rightarrow S_4$	74.07	25.00	25.82

Comparison to Prompting Baselines. Table 4 compares Cochain with IO, CoT, and ToT on proprietary backbones. While CoT and ToT enhance reasoning in a single-agent setting, they provide limited support for carrying stage constraints across a workflow. Cochain yields stronger generation quality under both GPT-3.5-turbo and GPT-4o. On GPT-3.5-turbo, Cochain increases BS-F from 72.84 (IO) to 76.94, demonstrating that the benefits go beyond deeper single-path reasoning.

Expert Evaluation and GPT-4 Scoring. Figure 3 provides external validation beyond automatic metrics. In panel (a), domain experts judge Cochain-augmented answers to be better in 40 cases and worse in 9 cases, with 51 cases considered similar. Panel (b) shows higher GPT-4 scores for settings augmented with Cochain, and the fine-tuned augmented setting reaches near-ceiling scores, corroborating the expert preference trend.

4.3 Key Design Factors

Ablation Study. To validate Cochain's effectiveness, we conduct ablation experiments with three variants: (1) w/o Knowledge Graph; (2) w/o Causal Chain; and (3) w/o Prompts Tree. As shown in Table 2, all variants exhibit performance degradation across all metrics, confirming each component's importance. Notably, removing the prompts tree causes the most significant drop, highlighting its critical role in collaboration.

Hyperparameter Influence. We vary two hyperparameters: prompt count and retrieval top-n from the knowledge graph. Figure 5 shows an inverted U-shape when increasing prompt count under fixed top-n, indicating an optimal prompt budget rather than monotonic gains. When fixing the prompt budget and varying top-n, the trend is also non-monotonic. Overall, performance is more sensitive to prompt budgeting than retrieving more nodes, consistent with Table 2, where Prompts Tree contributes most.

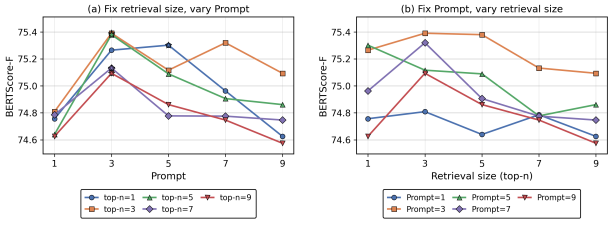
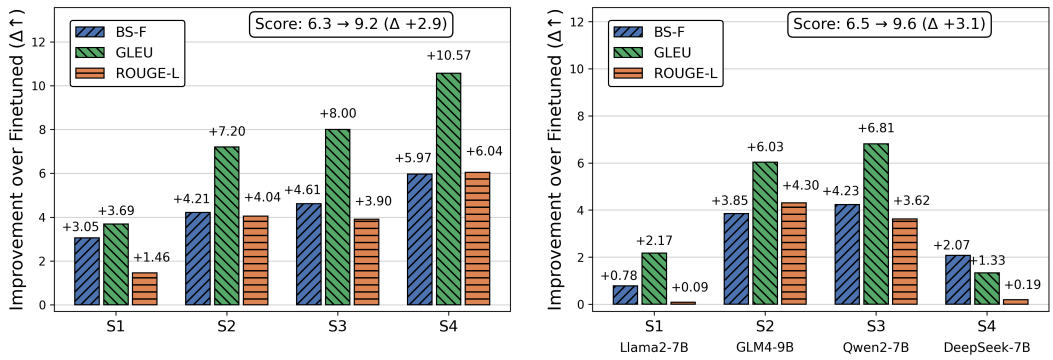


Figure 5: Hyperparameter influence of prompt budget and retrieval size. (a) Fix top-n retrieved nodes and vary prompt count. (b) Fix prompt count and vary top-n.

Stage Dependency. Table 5 shows that skipping any stage consistently degrades all metrics, indicating that each stage contributes non-redundant constraints for end-to-end workflow reasoning.

4.4 Cross-Domain and Specialized Settings

We evaluate Cochain on the Automotive workflow under two regimes: a jointly fine-tuned backbone trained on all stage data, and stage-wise fine-tuned backbones specialized per stage. Figure 6 reports stage-wise gains over the corresponding fine-tuned baselines, where Δ = +Cochain − Finetuned. With joint fine-tuning (Figure 6(a)), Cochain improves all stages and metrics, with larger gains in later stages where downstream constraints depend more on upstream decisions, indicating better constraint propagation without token-intensive interaction. With stage-wise fine-tuning (Figure 6(b)), Cochain



(a) Jointly fine-tuned backbone (Qwen2-7B) (b) Stage-wise fine-tuned backbones

Figure 6: Stage-wise gains of Cochain over fine-tuning on the Automotive workflow (Δ = +Cochain − Finetuned). (a) Jointly fine-tuned backbone (Qwen2-7B). (b) Stage-wise fine-tuned backbones. Bars show improvements in BS-F, GLEU, and ROUGE-L. Box reports the GPT-4 score gain of the integrated solution.

consistently boosts each specialized backbone, showing its ability to coordinate domain-expert agents into a coherent workflow solution. Integrated four-stage outputs also obtain higher GPT-4 scores in both regimes, supporting end-to-end quality gains beyond stage-local changes.

4.5 Efficiency and Cost Analysis

Figure 7 breaks down efficiency into one-time setup overhead and per-query running cost. Unlike interaction-heavy baselines, Cochain shifts most computation to offline setup and keeps inference lightweight. This yields consistent savings across budgets: for 1000 evaluation queries, Cochain consumes only 1.98M tokens, compared with 8.94M for CoA and 8.08M for Debate(long). The same trend appears in monetary cost, where Cochain costs $5.80 versus $18.20 and $20.12, and in wall-clock time, where Cochain finishes in 79,923s versus 253,184s and 574,949s. Although setup introduces an upfront cost, it is paid once and reused, so marginal cost grows slowly with more queries and the total advantage widens at scale. This shows that Cochain delivers high-quality solutions at low cost, effectively alleviating excessive collaboration.

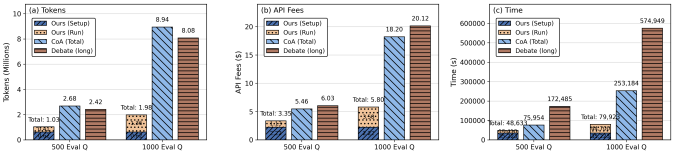


Figure 7: Cost comparison (Tokens, API Fees, Time) across baselines on pharmaceutical dataset. Cochain's total costs include the one-time Prompts Tree setup and costs for varying evaluation queries.

5 Conclusion

In this paper, we propose Cochain, a collaboration prompting framework that balances insufficient and excessive collaboration in LLM agent workflows. By bridging single-agent depth and multi-agent breadth through reusable collaboration artifacts, Cochain enables low-cost, fast, interpretable, and robust end-to-end reasoning. It builds prompts tree to distill stage-wise constraints and a cross-stage collaborative knowledge graph with counterfactual tacit knowledge, improving relational reasoning and reducing hallucinations. Its causal chain mechanism further exposes dependency traces for transparency and controllability. Experiments on specialized and cross-domain settings show consistent gains, and expert evaluation indicates that smaller Cochain-equipped models can outperform GPT-4.

AI USE STATEMENT

We did not use generative AI tools in any part of this work: neither for the tasks that require disclosure (generating synthetic datasets, developing theoretical models or conceptual frameworks, formulating mathematical claims or proofs, proposing or refining hypotheses, designing or evaluating the experimental methodology, implementing methods, translation, cleaning or reformatting data, qualitative or thematic analysis, or interpreting results) nor for the tasks with recommended disclosure (creating or editing figures, code or artifacts, drafting or editing the manuscript, literature search or summarization, or formatting references). All text, code, figures, data and analyses were produced by the authors, who take full responsibility for the content of this work.

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SUMMARY OF THE SUPPLEMENTARY MATERIAL

This appendix contains additional details for the paper. The appendix is organized as follows:

- § A describes algorithms and examples to better understand Cochain.
- § B describes the probabilistic formulations and mathematical proof for modeling an agent's unobservable tacit knowledge through the generation of counterfactual outputs.
- § C introduces more details on Cochain.
- § D presents more experiments and analysis on Cochain.
- § E provides a qualitative analysis to interpret the outputs of Cochain, alongside a comparative case study against baseline methods.
- § F presents the prompt templates for Cochain and other baselines.

A ALGORITHMS AND EXAMPLES TO BETTER UNDERSTAND COCHAIN

Algorithm 1: Collaborative Knowledge Graph Construction

Input: Datasets $D = \{D_1, \ldots, D_N\}$; LLM agents $A = \{A_1, \ldots, A_N\}$; evaluation LLM E; stage labels $L = \{L_1, \ldots, L_N\}$.
Output: A collaborative knowledge graph $\mathrm{KG}_{\text{collab}}$.

$\mathrm{KG}_{\text{explicit}} \leftarrow \emptyset$; $\mathrm{KG}_{\text{tacit}} \leftarrow \emptyset$;
// **Phase 1: Build Explicit Knowledge Graph**
for $i \leftarrow 1$ **to** N **do**
  foreach (*instruction*, *response*) $\in D_i$ **do**
    triples $\leftarrow$ ExtractTriples(instruction, response);
    LabelNodesInTriples(triples, L_i);
    $\mathrm{KG}_{\text{explicit}} \leftarrow \mathrm{KG}_{\text{explicit}} \cup$ triples;
// **Phase 2: Build Tacit Knowledge Graph**
for $i \leftarrow 1$ **to** N **do**
  foreach (*instruction*, *response*) $\in D_i$ **do**
    cf_instruction $\leftarrow$ GenerateCounterfactual(instruction);
    repeat
      cf_response $\leftarrow A_i$.query(cf_instruction);
      (evaluation, feedback) $\leftarrow E$.evaluate(cf_response);
      if *evaluation* $\neq$ *"reasonable"* **then**
        cf_instruction.append(feedback);
    until *evaluation* $=$ *"reasonable"*;
    tacit_triples $\leftarrow$ ExtractTriples(cf_instruction, cf_response);
    LabelNodesInTriples(tacit_triples, L_i);
    $\mathrm{KG}_{\text{tacit}} \leftarrow \mathrm{KG}_{\text{tacit}} \cup$ tacit_triples;
// **Phase 3: Merge Graphs**
$\mathrm{KG}_{\text{collab}} \leftarrow$ Merge($\mathrm{KG}_{\text{explicit}}, \mathrm{KG}_{\text{tacit}}$);
return KG_{collab};

Algorithm 2: Causal Chain Retrieval and Construction

Input: User query query; stage-labeled knowledge graph $\mathrm{KG}_{\text{collab}}$; text encoder Encoder; seed node count top_n; chain length limit max_depth.
Output: A textual causal chain causal_chain_text.
// **Phase 1: Two-Stage Seed Node Retrieval**
keywords $\leftarrow$ ExtractKeywords(query);
query_vector $\leftarrow$ Encoder.encode(query);
candidate_nodes $\leftarrow \mathrm{KG}_{\text{collab}}$.KeywordSearch(keywords);
candidate_vectors $\leftarrow$ Encoder.encode(candidate_nodes);
similarities $\leftarrow$ CosineSimilarity(query_vector, candidate_vectors);
seed_nodes $\leftarrow$ GetTopN(candidate_nodes, similarities, top_n);
// **Phase 2: Stage-Aware Multi-hop Expansion**
all_paths $\leftarrow \emptyset$;
foreach start_node $\in$ seed_nodes **do**
  // Search paths crossing stages via bridge nodes with multiple labels
  paths $\leftarrow \mathrm{KG}_{\text{collab}}$.FindCrossStagePaths(start_node, min_depth $\leftarrow 2$, max_depth);
  all_paths $\leftarrow$ all_paths $\cup$ paths;
// **Phase 3: Format and Output**
causal_chain_text $\leftarrow$ VerbalizePaths(all_paths);
return causal_chain_text;

Algorithm 3: Prompts Tree Construction

Input: Workflow stages $S = \{S_1, \ldots, S_n\}$; domain agents $A = \{A_1, \ldots, A_n\}$; seed Q-A pair InitialSeedQA; best prompt count m.
Output: A prompt tree PromptsTree.

```
// Initialize
rootNode ← CreateNode(InitialSeedQA.question);
PromptsTree ← InitializeTree(rootNode);
queue ← [(rootNode, InitialSeedQA.answer, S_1)];
while queue ≠ ∅ do
    (parentNode, currentAnswer, currentStage) ← queue.pop_front();
    // Phase 1: Distill Prompts
    distilledPrompts ← A_currentStage.DistillPrompts(currentAnswer);
    // Phase 2: Select Best Prompts
    bestPrompts ← A_currentStage.SelfEvaluate(distilledPrompts, m);
    // Phase 3: Grow Tree
    if currentStage ≠ S_n then
        nextStage ← S_index(currentStage)+1;
        foreach promptText ∈ bestPrompts do
            childNode ← CreateNode(promptText);
            parentNode.add_child(childNode);
            newQuestion ←
              GenerateQuestionForNextStage(promptText, nextStage);
            newAnswer ← A_nextStage.query(newQuestion);
            queue.push_back((childNode, newAnswer, nextStage));
return PromptsTree;
```

As shown in the Figure 9, after applying Cochain, the agent anticipates that carbon fiber requires complex molding processes, completely different from traditional metal stamping, and that qualified suppliers are scarce, thus requiring consideration of supply chain stability and high procurement costs significantly impacting vehicle pricing and profit margins. The prompts tree anticipates existing production processes, guiding the agent to consider compatibility constraints between new equipment and existing stamping-welding lines. Based on this, Cochain generates superior answers compared to single agents.

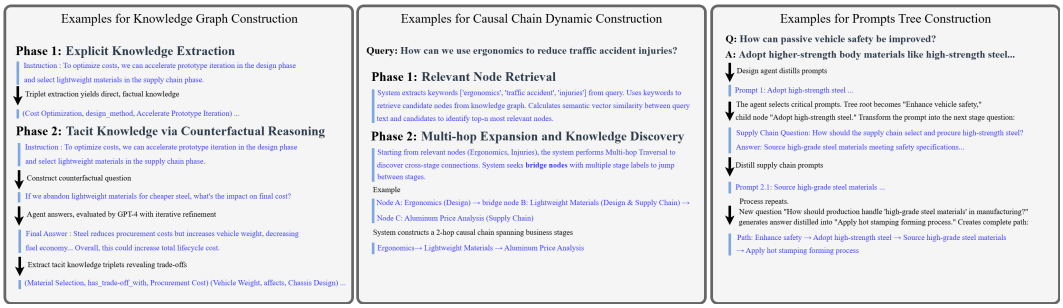

Figure 8: Examples of implementing a core component in the Cochain framework.

Q: To improve fuel economy, the design team recommends that the new vehicle model adopt carbon fiber materials to replace steel. What is your recommendation?

Examples of Single Agent

A: Carbon fiber is an ideal choice. It is 60% lighter than steel, 5 times stronger, and has excellent corrosion resistance, which can significantly improve fuel economy and handling. In addition, carbon fiber has a highly technological appearance and is an iconic material for luxury models. Therefore, it is recommended to adopt it comprehensively to maximize performance advantages.

Examples of Complete Workflow of Cochain

Cochain's working mechanism: first retrieves knowledge graphs and performs causal chain exploration, then prompts tree retrieval.

Knowledge Graphs Retrieval

(Lightweight, improves, fuel economy)
(Carbon fiber, property, lightweight)
(Carbon fiber, property, high strength)
(Carbon fiber, requires, complex molding process)
(Carbon fiber, faces, scarce suppliers)
...

Causal Chain

Carbon fiber requires complex molding process, complex molding process relates to redesigning connection structures; Complex molding process requires new curing equipment, new curing equipment considers compatibility with stamping lines ...

Prompts Tree

User Need: New material application → Design: Analyze design impacts and challenges → Supply Chain: Assess supply chain feasibility → Production: Consider existing production processes → QI: Establish quality standards for new materials; User Need: Improve fuel economy → Design: Lightweight body design → Supply Chain: Assess supply chain feasibility → Production: Improve production processes to ensure processing quality → QI: Inspect product quality after production process improvements ...

Answer by Cochain

We recommend adopting a phased strategy, first validating carbon fiber processes on non-structural components such as spoilers and interior panels, and then expanding after costs become controllable. In design, although lightweight effects are good, **the molding process is complex, requiring redesign of connection structures and crash energy absorption zones**; the supply chain **faces challenges of scarce suppliers, prices far exceeding steel, and long procurement cycles**; production requires **investment in new curing equipment and consideration of compatibility with existing stamping lines**; quality control requires **addition of new inspection items such as fiber direction and curing degree**.

Figure 9: Examples of single agent and complete workflow of Cochain

B PROOF: TACIT KNOWLEDGE & COUNTERFACTUAL OUTPUT MODEL

Given the inherent difficulty in directly extracting hidden layer knowledge from agents operating within complex systems, our approach introduces counterfactual reasoning as a means to probe and subsequently infer tacit knowledge. This section elucidates the probabilistic formulations developed to model these inferred internal aspects of each agent. It details the conceptualization of tacit knowledge, the generation of counterfactual outputs by the agent, and the overall generative process used to understand these unobservable agent workings.

The foundation of our approach to modeling tacit knowledge within each agent lies in its conditional generation based on latent tacit variables. We define h_{ij} as the tacit knowledge specific to a sample (X_{ij}, Y_{ij}) processed by a particular agent. Within an agent, h_{ij} represents an internal state or representation that is not directly accessible. While h_{ij} is an abstract construct for modeling these unobservable aspects, for illustrative purposes, one might conceptualize it as akin to intermediate computational states, learned feature representations, or internal configurations within the Agent that influence its output generation. Concurrently, θ_{ij} is defined as a latent tacit variable associated with the same sample and agent. This variable θ_{ij} is also an abstract construct, encapsulating underlying factors hypothesized to influence h_{ij}, such as specific input characteristics processed by the Agent, its operational modes, or conditioning contexts it operates under. The introduction of θ_{ij} and h_{ij} is an attempt to create a probabilistic model for the Agent's internal, unobservable precursors to decision-making or generation.

A core assumption of our model is that this tacit knowledge h_{ij} is not deterministically derived but is rather a stochastic realization conditioned on θ_{ij}. This is particularly relevant for complex Agents, where output generation can be influenced by internal stochastic mechanisms or intricate decision processes. This probabilistic relationship is formally expressed as:

$$h_{ij} \mid \theta_{ij} \sim P(h_{ij} \mid \theta_{ij}). \tag{8}$$

This notation signifies that h_{ij} is a random variable whose probability distribution $P(h_{ij} \mid \theta_{ij})$ is conditional upon the specific value or state of θ_{ij}. The nature of this distribution would be specific to the agent and reflects the inherent complexities and uncertainties in how its internal states are formed. For instance, θ_{ij} might represent an abstract control signal or a high-level interpretation of input patterns by the agent, and $P(h_{ij} \mid \theta_{ij})$ would describe the distribution of possible internal representations resulting from it. This formulation acknowledges that even with a defined influencing factor θ_{ij}, the precise tacit knowledge h_{ij}, namely the agent's internal processing focus or state, can vary. The characteristics of $P(h_{ij} \mid \theta_{ij})$ can be explored and potentially learned through systematic counterfactual probing of the agent.

Following the generation of tacit knowledge, we model the generation of the counterfactual output $\tilde{Y}_{ij}$ by the agent. This output is conditioned not only on the counterfactual input $\tilde{X}_{ij}$ but also critically on the realized tacit knowledge h_{ij} derived from Equation 8. We define $\tilde{Y}_{ij}$ as the Agent's generated output when presented with the counterfactual input $\tilde{X}_{ij}$, and h_{ij} acts as the mediating internal state through which $\tilde{X}_{ij}$ is processed to produce $\tilde{Y}_{ij}$.

The generation of $\tilde{Y}_{ij}$ by such agents is often an inherently probabilistic process. Even with a given counterfactual input $\tilde{X}_{ij}$ and a specific internal tacit knowledge state h_{ij}, the agent may not produce a single, deterministic output. This inherent stochasticity is captured by the following conditional probability distribution, whose parameters might also be inferred from counterfactual observations:

$$\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij} \sim P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij}). \tag{9}$$

This expression states that $\tilde{Y}_{ij}$, the counterfactual output, is a random variable whose distribution $P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij})$ depends on both the specific tacit knowledge state h_{ij} and the counterfactual input $\tilde{X}_{ij}$. The tacit knowledge h_{ij} here serves as a crucial intermediary. For agents producing sequential outputs, $P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij})$ might be represented as an autoregressive factorization:

$$P(\tilde{Y}_{ij} \mid h_{ij}, \tilde{X}_{ij}) = \prod_{t} P(\tilde{y}_{ij,t} \mid \tilde{y}_{ij,<t}, h_{ij}, \tilde{X}_{ij}).$$

To determine the overall probability of observing a counterfactual output $\tilde{Y}_{ij}$ from an agent given only the counterfactual input $\tilde{X}_{ij}$, a common scenario when internal states are not directly observable,

we must account for the entire hypothesized generative pathway. This involves marginalizing out the unobserved latent tacit variable θ_{ij} and, by extension, the intermediate tacit knowledge h_{ij}.

For compactness in the following derivation, let $\widetilde{Y} = \tilde{Y}_{ij}$, $\widetilde{X} = \tilde{X}_{ij}$, $h = h_{ij}$, and $\theta = \theta_{ij}$. The final generation process is thus expressed as:

$$P(\widetilde{Y} \mid \widetilde{X}) = \int_{\Theta} P(\widetilde{Y} \mid h, \widetilde{X}) \cdot P(h \mid \theta) P(\theta \mid \widetilde{X})\, d\theta. \tag{10}$$

This equation can be derived by considering the dependencies established in Equations 8 and 9.

The derivation proceeds as follows. First, we apply the law of total probability to marginalize over the latent tacit variable θ. The probability of $\widetilde{Y}$ given $\widetilde{X}$ can be written as an integral over all possible values of θ in its domain Θ:

$$P(\widetilde{Y} \mid \widetilde{X}) = \int_{\Theta} P(\widetilde{Y}, \theta \mid \widetilde{X})\, d\theta.$$

Using the definition of conditional probability, $P(A, B \mid C) = P(A \mid B, C) P(B \mid C)$, we can rewrite the integrand $P(\widetilde{Y}, \theta \mid \widetilde{X})$ as:

$$P(\widetilde{Y}, \theta \mid \widetilde{X}) = P(\widetilde{Y} \mid \theta, \widetilde{X}) \cdot P(\theta \mid \widetilde{X}).$$

Here, $P(\theta \mid \widetilde{X})$ represents the prior probability distribution of the tacit variable θ given the counterfactual input $\widetilde{X}$. This term reflects how a given counterfactual input might stochastically lead to different internal configurations or "operational modes" θ within the Agent that are not directly observable. The nature of this prior can also be investigated through counterfactual analysis.

Substituting this back, we get:

$$P(\widetilde{Y} \mid \widetilde{X}) = \int_{\Theta} P(\widetilde{Y} \mid \theta, \widetilde{X}) \cdot P(\theta \mid \widetilde{X})\, d\theta. \tag{11}$$

The term $P(\widetilde{Y} \mid \theta, \widetilde{X})$ is the probability of generating $\widetilde{Y}$ given both θ and $\widetilde{X}$. Our model posits a specific structure for this, reflecting a Markov chain-like dependency: $\theta \to h \to \widetilde{Y}$, all conditioned on $\widetilde{X}$ where appropriate. This structure implies two key conditional independence assumptions:

1. Given θ, h is independent of $\widetilde{X}$ if all influence of $\widetilde{X}$ on h is mediated through θ. More commonly, $P(h \mid \theta)$ is defined as the direct influence of θ on h.
2. Given h and $\widetilde{X}$, $\widetilde{Y}$ is independent of θ. That is, $P(\widetilde{Y} \mid h, \theta, \widetilde{X}) = P(\widetilde{Y} \mid h, \widetilde{X})$. The tacit knowledge h fully mediates the influence of θ on $\widetilde{Y}$.

Under these assumptions, we can decompose $P(\widetilde{Y} \mid \theta, \widetilde{X})$ as:

$$\begin{aligned} P(\widetilde{Y} \mid \theta, \widetilde{X}) &= \int P(\widetilde{Y}, h \mid \theta, \widetilde{X})\, dh \\ &= \int P(\widetilde{Y} \mid h, \theta, \widetilde{X}) \cdot P(h \mid \theta, \widetilde{X})\, dh \\ &= \int P(\widetilde{Y} \mid h, \widetilde{X}) \cdot P(h \mid \theta)\, dh. \end{aligned}$$

The form in Equation 10 implies that for a given θ in the outer integral, the relevant h is the one generated from that θ, effectively collapsing the inner integral. Thus, $P(\widetilde{Y} \mid \theta, \widetilde{X})$ is represented by the product $P(\widetilde{Y} \mid h, \widetilde{X}) P(h \mid \theta)$, where h is the specific realization tied to θ within the integral.

Substituting this construction into Equation 11 directly yields Equation 10:

$$P(\widetilde{Y} \mid \widetilde{X}) = \int_{\Theta} P(\widetilde{Y} \mid h, \widetilde{X}) \cdot P(h \mid \theta) P(\theta \mid \widetilde{X})\, d\theta.$$

This integral sums the probabilities of $\widetilde{Y}$ occurring via all possible latent tacit variables θ. Each path's contribution is weighted by the prior probability of θ, the probability of the corresponding tacit knowledge h arising from that θ, and finally the probability of the output $\widetilde{Y}$ given that h and the input $\widetilde{X}$.

C Implementation Details

Definition of Business Workflow: It is a complex process with many interconnected stages. These stages are specialized. The key feature is that these stages strongly depend on each other. A decision in one stage requires more than just expert knowledge of that area. It must also anticipate and use knowledge and constraints from the other stages.

Table 6 presents a comprehensive comparison of Cochain against other baseline models. Cochain demonstrates superior agent collaboration, characterized by faster inference speeds and lower hallucination rates. More critically, Cochain exhibits decomposability, ensuring that the collaboration process is resilient and does not terminate due to failures in individual components. It is important to note that for CoA, source documents are not included due to the differing task orientation.

The LLMs referenced in Figure 4 (Main Paper) are fine-tuned using QLoRA (Dettmers et al., 2023), configured with a LoRA rank of 8 and trained for 3 epochs, on two H100 GPUs, with models quantized to 4-bit precision via bitsandbytes. Other open-source models are fine-tuned for 10 epochs using LoRA (Hu et al., 2022). The inference times reported in Figure 10 and Table 7 are benchmarked by deploying the open-source models on a single A40 GPU to mitigate network variability.

Table 6: Comparison of different multi-agent collaboration methods

Baseline	Collaboration Method	Decomposable	Reasoning Speed	Hallucination Rate	Agent
PMC (Zhang et al., 2025a)	Hierarchical Planning	✗	Low	Middle	Multiple
MedAgents (Tang et al., 2024)	Discussion & Voting	✗	Low	Middle	Multiple
Debate(short) (Du et al., 2024)	Debate	✗	Low	Middle	Multiple
Debate(long) (Du et al., 2024)	Debate	✗	Low	Middle	Multiple
CoA (Zhang et al., 2024b)	Chain Collaboration	✗	Low	Middle	Multiple
Original	-	✓	High	High	Single
Cochain	Knowledge Fusion	✓	High	Low	Multiple

The appendix provides a more extensive report on experimental results across additional metrics. These include BERTScore-P, BERTScore-R, BLEU-4 (Papineni et al., 2002) for measuring text alignment, METEOR (Banerjee & Lavie, 2005) which considers semantically equivalent phrases, ROUGE-2 for assessing content breadth, and ROUGE-L (Lin, 2004) which evaluates deep semantic alignment, particularly for long texts.

D More Experiments and Analysis

D.1 More Efficiency and Cost Analysis

Table 7 presents a comparative analysis of Cochain against other multi-agent systems, focusing on key operational metrics: Inference Time, Token Throughput, and Cost. A noteworthy observation on the Automotive and E-commerce datasets is that Cochain's average input token count is approximately one-twentieth of that utilized by PMC and CoA. This disparity suggests that these alternative systems expend a considerable volume of tokens on inter-agent communication. In contrast, Cochain innovatively transforms such communication into structured knowledge graphs and prompts tree, a mechanism that effectively curtails operational costs. The overall results compellingly demonstrate that Cochain achieves substantial reductions in inference time, token throughput, and aggregate cost

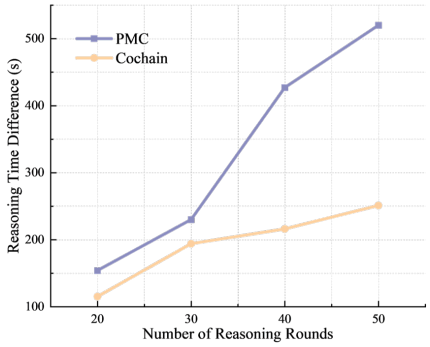

Figure 10: ExampReasoning time differential.

Table 7: Comparative analysis of inference time, token throughput, and cost. †Inference time is measured using a locally deployed Qwen2-7B model to obviate network latency associated with API calls. Conversely, token throughput and cost metrics are derived using Claude-3.5-Haiku.

Baselines	†Inference Time (s)	Avg.Input	Avg.Output	Avg.Cost ($)
Automotive				
PMC (Zhang et al., 2025a)	241.56	11637.94	6644.22	0.0359
MedAgents (Tang et al., 2024)	196.53	3901.03	3483.24	0.0170
Debate(short) (Du et al., 2024)	187.16	3938.35	4809.27	0.0223
Debate(long) (Du et al., 2024)	162.57	4357.87	5278.53	0.0246
CoA (Zhang et al., 2024b)	227.21	11428.06	5446.62	0.0309
Original	37.22	93.49	1041.38	0.0042
Cochain	38.77	501.62	541.74	**0.0026**
Pharmaceutical				
PMC (Zhang et al., 2025a)	198.49	3796.07	2613.73	0.0135
MedAgents (Tang et al., 2024)	169.53	3504.85	3504.85	0.0168
Debate(short) (Du et al., 2024)	548.66	3372.56	3772.79	0.0178
Debate(long) (Du et al., 2024)	574.95	3810.87	4268.74	0.0201
CoA (Zhang et al., 2024b)	253.18	5493.94	3450.45	0.0182
Original	60.96	77.28	1091.32	0.0044
Cochain	44.70	533.88	830.34	**0.0037**
E-commerce				
PMC (Zhang et al., 2025a)	256.84	11319.74	6452.89	0.0349
MedAgents (Tang et al., 2024)	181.61	3816.26	3445.34	0.0169
Debate(short) (Du et al., 2024)	318.51	4414.23	5660.94	0.0261
Debate(long) (Du et al., 2024)	293.42	5438.52	6911.85	0.0321
CoA (Zhang et al., 2024b)	195.49	11446.05	5353.24	0.0306
Original	35.83	60.90	1080.92	0.0044
Cochain	37.10	561.80	620.15	**0.0029**

when benchmarked against other multi-agent approaches. **Remarkably, the efficiency metrics for Cochain closely approximate those observed for single-agent systems, and its average cost is even lower**, underscoring a significant advantage of our proposed framework in terms of computational resource utilization and operational expenditure. Table 8 presents the retrieval contribution of each component during the inference process. The prompt tree retrieval employs a depth-first search (DFS) strategy. In terms of time complexity, this is equivalent to a simple path traversal with a complexity of $O(D)$, where D denotes the depth of the business process. Figure 10 shows that as reasoning rounds increase, the time gap between thinking and non-thinking models grows dramatically for PMC but remains moderate for Cochain, demonstrating Cochain's superior efficiency as complexity increases.

Table 8: Latency Breakdown Analysis of Cochain's Inference Components

Inference Component	**Average Time (s)**	**Percentage of Total Time (%)**
Knowledge Graph Retrieval	0.6200 s	1.57 %
Prompts Tree Retrieval	0.0022 s	<0.01 %
LLM Model Inference	38.7700 s	98.42 %

D.2 More Experiments on Single Agent

Table 9 and Table 10 demonstrate that integrating Cochain markedly enhances single-agent performance across diverse backbone models during two distinct stages of a business workflow. This enhancement is consistently reflected across all evaluated metrics, irrespective of whether the LLMs are in their raw, pre-trained state or have undergone fine-tuning. Notably, a synergistic effect between fine-tuning and the application of Cochain typically yields optimal performance, underscoring Cochain's robust capability to leverage specialized model knowledge. The broad-spectrum improvements observed across various model metrics highlight the effectiveness and versatility of Cochain in mitigating prior issues of insufficient collaboration.

Table 9: The performance of our proposed method on single-agent. BERTScore F1 is abbreviated as BS-F, BERTScore Precision as BS-P, and BERTScore Recall as BS-R. We highlight the best and second-best results.

Backbone	Method	BS-F	BS-P	BS-R	BLEU-4	GLEU	METEOR	ROUGE-2	ROUGE-L
Llama2-7B	Raw LLM	62.25	64.41	60.54	6.04	8.28	17.52	7.78	15.64
	+ Cochain	65.70	68.25	63.50	10.99	13.84	25.50	10.44	16.46
	Finetuned LLM	70.68	70.71	70.67	14.31	18.79	35.03	11.97	21.49
	+ Cochain	71.46	71.35	71.59	16.50	20.96	38.69	13.79	21.58
Qwen2-7B	Raw LLM	71.76	71.79	71.75	17.23	22.30	41.13	12.88	24.00
	+ Cochain	75.24	74.90	75.58	22.32	26.51	52.00	19.53	27.94
	Finetuned LLM	71.72	71.75	71.70	16.90	21.64	40.77	13.35	24.07
	+ Cochain	75.39	75.14	75.65	24.17	28.17	51.22	21.22	28.87
Llama3-8B	Raw LLM	68.93	68.38	69.59	7.47	9.14	24.48	10.99	19.28
	+ Cochain	73.75	73.36	74.17	19.47	23.52	48.43	17.57	25.10
	Finetuned LLM	70.89	70.88	70.91	14.90	19.05	39.83	12.59	22.90
	+ Cochain	74.56	74.13	75.01	22.12	26.15	50.59	19.41	27.19
Llama2-13B	Raw LLM	60.79	63.16	59.00	5.73	7.96	16.90	7.52	15.43
	+ Cochain	67.47	70.20	65.15	13.42	16.88	29.97	13.65	18.57
	Finetuned LLM	70.88	70.88	70.90	14.57	19.14	35.87	12.19	21.85
	+ Cochain	71.80	72.08	71.58	18.16	22.29	40.33	14.96	23.18
Qwen2.5-14B	Raw LLM	71.86	72.03	71.70	9.48	12.16	40.71	11.85	17.86
	+ Cochain	75.62	75.56	75.69	12.39	14.71	47.95	17.66	19.55
	Finetuned LLM	71.50	71.48	71.53	9.25	11.75	40.16	12.01	17.67
	+ Cochain	75.18	75.00	75.38	13.11	15.08	48.35	19.70	20.30

Table 10: The performance of our proposed method. The results of this table are in a different stage, as compared to the stage presented in Table 9. We highlight the best and second-best results.

Backbone	Method	BS-F	BS-P	BS-R	BLEU-4	GLEU	METEOR	ROUGE-2	ROUGE-L
Llama2-7B	Raw LLM	61.76	64.72	59.44	6.36	8.69	18.25	8.66	16.17
	+ Cochain	63.57	66.31	61.23	9.49	12.37	23.12	8.99	17.46
	Finetuned LLM	69.88	69.78	70.00	12.02	17.02	32.59	9.26	20.69
	+ Cochain	70.47	70.43	70.55	13.79	18.58	35.44	10.91	20.26
Qwen2-7B	Raw LLM	70.34	71.12	70.60	13.74	19.88	35.29	9.47	22.01
	+ Cochain	73.48	72.37	74.63	15.77	19.21	50.38	16.25	21.99
	Finetuned LLM	70.28	70.08	70.50	13.61	18.95	35.07	9.96	22.38
	+ Cochain	74.51	74.30	74.74	21.99	25.76	50.49	20.71	26.00

As shown in Table 11, to better quantify the impact of insufficient collaboration, we compare the baseline single agent to one provided with minimal communication, simulated by manually injecting

Table 11: Quantifying insufficient collaboration.

Backbone	Method	BS-F	GLEU	ROUGE-L
Qwen2-7B	Single Agent	71.72	21.64	24.07
	+ Manual Prompts	72.54 (↑)	21.83 (↑)	24.34 (↑)
	+ Cochain	**75.39** (⇑)	**28.17** (⇑)	**28.87** (⇑)
DeepSeek-R1-7B	Single Agent	71.35	19.55	22.71
	+ Manual Prompts	71.83 (↑)	19.90 (↑)	23.38 (↑)
	+ Cochain	**73.19** (⇑)	**21.71** (⇑)	**24.01** (⇑)

five prompts containing cross-domain constraints. The results of this table clearly show: First, insufficient collaboration is a real problem, as the agent with injected communication showed a slight performance improvement over the original agent. This directly proves that adding cross-domain communication improves outcomes, thereby quantifying the performance loss from insufficient collaboration. Second, Cochain's intelligent collaboration is far superior to simple communication, as the performance improved substantially after applying Cochain. This demonstrates that Cochain's value is not just about adding information. Rather, it excels at intelligently filtering, organizing, and structuring collaborative knowledge. Its effectiveness far surpasses that of unstructured, manually added information and helps to avoid the risk of excessive collaboration.

D.3 More Experiments on Specialized Agent Collaboration

Figure 6 (Main Paper) presents the results from a distinct experimental configuration designed to further investigate the coordination capabilities of Cochain. Whereas Table 9 assessed a multi-domain model (a single Qwen2-7B model fine-tuned on all domains) and specialized models (different models each fine-tuned for specific domains), Table 12 exclusively focuses on a setup utilizing multiple agents of the same backbone, each independently fine-tuned for a specific domain. The findings indicate that Cochain effectively facilitates collaboration among these identically architected yet uniquely specialized agents. Performance enhancements are observed both within their respective specialized domains and in the quality of the comprehensive, integrated solutions. This underscores Cochain's distinct advantage in synergizing specialized knowledge from a team of uniquely trained agents that share a common architectural foundation.

Table 12: Results for one model at particular stages. This means that we use Qwen2-7B for four fine-tunings, and the four fine-tuned models are experimented with at their respective stages. We highlight the fine-tuned results, Cochain application, and improvements(↑).

Backbone	Stage	Method	BS-F	BS-P	BS-R	BLEU-4	GLEU	ROUGE-L
Qwen2-7B	S_1	Finetuned	71.72	71.75	71.70	16.90	21.64	24.07
		+ Cochain	75.39	75.14	75.65	24.17	28.17	28.87
		↑	+3.67	+3.39	+3.95	+7.27	+6.53	+4.80
	S_2	Finetuned	70.24	70.47	70.16	13.19	18.29	20.95
		+ Cochain	74.23	74.01	74.46	20.05	23.57	24.71
		↑	+3.99	+3.54	+4.30	+6.86	+5.28	+3.76
	S_3	Finetuned	70.28	70.08	70.50	13.61	18.95	22.38
		+ Cochain	74.51	74.30	74.74	21.99	25.76	26.00
		↑	+4.23	+4.22	+4.24	+8.38	+6.81	+3.62
	S_4	Finetuned	69.40	69.49	69.32	13.51	18.26	21.82
		+ Cochain	75.06	74.99	75.15	23.95	27.70	27.49
		↑	+5.66	+5.50	+5.83	+10.44	+9.44	+5.67
Score			6.4		9.5		+3.1	

D.4 More Results from Ablation Studies

On the automotive dataset, we report additional ablation study results focusing on the impact of different backbone models. As indicated in Table 13, "w/o Prompts Tree" markedly impaired performance. Specifically, when applied to the Llama-8B backbone, this ablation led to a 1.97% reduction in the BS-F score, with notable degradations also observed across other evaluation metrics. These findings are consistent with the experimental results presented in Table 2 (Main Paper), further underscoring the critical role of the Prompts Tree component in our framework.

Table 13: More results of the ablation study. $\mathcal{CKG}$ represents the collaborative knowledge graph. We highlight the most and second-most efficient modules.

Backbone	Method	BS-F	BS-P	BS-R	BLEU-4	GLEU	METEOR	ROUGE-2	ROUGE-L
Llama2-7B	Cochain	71.46	71.35	71.59	16.50	20.96	38.69	13.79	21.58
	w/o $\mathcal{CKG}$	71.26	71.14	71.41	16.06	20.53	38.21	13.55	21.50
	w/o Causal Chain	71.26	71.13	71.44	15.63	19.59	40.32	14.33	21.16
	w/o Prompts Tree	71.06	70.92	71.20	15.20	19.61	36.66	13.07	21.38
Qwen2-7B	Cochain	75.39	75.14	75.65	24.17	28.17	51.22	21.22	28.87
	w/o $\mathcal{CKG}$	75.21	74.91	75.53	23.56	27.81	49.76	20.15	28.74
	w/o Causal Chain	75.20	74.92	75.50	23.68	27.55	51.00	21.14	28.42
	w/o Prompts Tree	73.08	73.20	72.98	18.40	22.45	45.43	16.06	24.56
Llama3-8B	Cochain	74.56	74.13	75.01	22.12	26.15	50.59	19.41	27.19
	w/o $\mathcal{CKG}$	74.27	73.80	74.75	21.45	25.46	49.99	19.09	27.13
	w/o Causal Chain	73.63	72.79	74.50	17.34	20.70	49.15	18.28	23.78
	w/o Prompts Tree	72.59	72.45	72.75	17.01	21.02	45.00	15.18	23.83
Qwen2.5-14B	Cochain	75.18	75.00	75.38	13.11	15.08	48.35	19.70	20.30
	w/o $\mathcal{CKG}$	74.83	74.41	75.25	12.49	14.55	47.32	18.39	19.76
	w/o Causal Chain	74.71	74.66	74.79	12.28	14.17	47.65	19.30	19.44
	w/o Prompts Tree	73.01	73.01	73.02	9.98	12.25	42.72	14.15	18.00

D.5 Integration of Cochain with Baselines

We further investigate the integration of Cochain with existing baseline methods, specifically PMC and MedAgents, through experiments conducted on a pharmaceutical dataset using Claude-3.5-Haiku. As reported in Table 14, the combination of Cochain with PMC results in improvements of 2.62% and 7.55% in the BS-F and BLEU-4 scores, respectively. This outcome further substantiates the efficacy of Cochain in mitigating issues associated with excessive collaboration.

Table 14: The improvement of Cochain over other baselines on pharmaceutical datasets.

Baseline	BS-F	BS-P	BS-R	BLEU-4	GLEU	METEOR	ROUGE-2	ROUGE-L
PMC (Zhang et al., 2025a)	66.51	66.06	66.97	5.17	12.33	20.31	5.48	13.56
PMC (Zhang et al., 2025a) + Cochain	**69.13**	**68.49**	**69.80**	**12.72**	**18.48**	27.01	**6.93**	**15.82**
MedAgents (Tang et al., 2024)	66.23	66.02	66.48	7.17	14.02	22.59	5.43	14.32
MedAgents (Tang et al., 2024) + Cochain	67.45	66.91	68.00	11.65	17.80	**27.06**	6.16	15.74

D.6 Evaluation of Collaborative Knowledge Graph

To evaluate the reliability of our final knowledge graph, we randomly sampled 2,000 triplets from it, consisting of 1,000 from explicit knowledge extraction and 1,000 from our counterfactual method. We used three core metrics for evaluation: Factual Correctness (Is the knowledge factually correct in the real world?),Task Relevance (How helpful is the knowledge for solving business workflow problems?), and Knowledge Depth (Is the knowledge common sense, or does it require professional insight?) We invited two domain experts for a blind review. We also used Gemini-2.5-Pro as a judge for an objective evaluation. The average scores (out of 5) are presented in the Table 15.

D.7 Excessive collaboration is More Serious than Insufficient collaboration

Business workflow tasks are particularly susceptible to the "excessive collaboration" phenomenon. When multiple agents collaborate, this manifests as responses deviating from core issues and reducing

Table 15: Evaluation of Collaborative Knowledge Graphs by Human Experts and LLMs.

Evaluation Metric	Human Expert Score (Avg. / 5.0)	Gemini-2.5-Pro Score (Avg. / 5.0)
Factual Correctness	4.99	5.00
Task Relevance	4.76	4.81
Knowledge Depth	4.31	4.54

answer quality. Comparative analysis of Table 1 (Main Paper), Figure 6 (Main Paper), and additional single-agent experimental results (Supplementary Material D.2) demonstrates that, despite consuming significantly more computational resources, excessive collaboration performs substantially worse than insufficient collaboration. excessive collaboration's challenging nature is its covertness—systems maintain high activity and apparent collaboration, making the problem hard to detect and rectify promptly. While task decomposition, such as approaches like PMC, and summarization, such as strategies like CoA, are considered effective methods for focusing on core issues (Wu et al., 2024; Chen et al., 2024), Cochain's collaboration mechanism exhibits superior performance in controlling excessive collaboration, enabling a more precise focus on critical task requirements.

D.8 Robustness to Incomplete Retrieval

To validate the system's robustness against potential keyword retrieval failures, we conducted a stress test. We designed 50 structured queries in the format of "How to use [Core Concept A] to solve problems related to [Target Concept B]". In the test condition, we deliberately masked all keywords corresponding to [Target Concept B] to simulate a first-stage retrieval failure. For instance, in the query "How can ergonomics be used to reduce traffic accident injuries?", the keywords "traffic" and "accident" were blocked.

While end-to-end semantic retrieval could theoretically solve keyword-mismatch issues, it becomes computationally prohibitive for real-time interaction on massive knowledge graphs. We therefore adopt the Retrieval-Ranking two-stage paradigm, a proven industry standard (Covington et al., 2016). This approach combines the advantages of both methods: keyword-based retrieval in the first stage ensures precise matching of technical terms and proper nouns, avoiding omissions from semantic over-generalization. In the second stage, semantic ranking captures the query's overall intent, ensuring system generalization and robustness.

Table 16: Performance comparison under simulated retrieval failure. Masking the target concept's keywords results in a negligible performance drop, demonstrating the system's robustness.

Test Condition	BS-F	GLEU	ROUGE-L
Full Query	74.16	22.08	25.86
Target Concept Masked	73.87	21.42	24.57
Performance Drop (%)	**-0.29%**	**-0.66%**	**-1.29%**

The results in Table 16 confirm the effectiveness of this design. Even when forcing a first-stage failure, the BS-F score experienced a minimal drop of only 0.29%, from 74.16 to 73.87, with similarly small decreases in GLEU (-0.66%) and ROUGE-L (-1.29%) scores. This resilience is attributed to two factors. First, as justified above, the semantic ranking stage corrects for an imperfect initial candidate set. More critically, the subsequent graph traversal and causal chain stages provide a powerful secondary path to completeness. Even if "Traffic Accident" is missed during retrieval, it can be discovered through pre-existing knowledge paths represented as triples (e.g., (Injuries, is_a_result_of, Traffic Accident)), ensuring the final context remains robust and comprehensive.

E CASE STUDY

E.1 INTERPRETABILITY ANALYSIS

We investigate the interpretability characteristics of the model after the application of Cochain through a case study. As shown in Table 17, we employ the same color to annotate logically related content visually. The findings reveal that, following the application of Cochain, the model is capable of performing multi-dimensional reasoning based on knowledge graphs, causal inference chains, and contextual cues when addressing user needs, thereby generating outputs that are traceable, reliable, and interpretable. The application of the Cochain method has significantly enhanced the transparency and explainability of the model's reasoning process, providing empirical evidence for understanding the model's collaborative decision-making mechanisms.

E.2 COMPARATIVE ANALYSIS OF MODEL OUTPUTS

To understand how different baselines handle complex instructions, as shown in Figure 11, we qualitatively analyzed their outputs against a reference answer, focusing on their integration of User Experience(UX) design within the automotive business workflow. Additionally, we present case studies for the pharmaceutical business workflow and the e-commerce business workflow, as shown in Figure 12 and Figure 13.

Cochain: Clear Structure, Focused on UX Integration Process. Cochain's response was notably well-structured, using a seven-point list for key UX integration stages, enhancing readability and providing a clear action framework. It comprehensively covered the UX lifecycle—from user research and design principles to interdisciplinary collaboration, technological innovation, continuous iteration, and performance-cost/quality assurance. Its explicit "collaborative perspective of the automotive business workflow" aligned with the reference answer's holistic view, effectively capturing its spirit by offering a structured, UX-centric methodology.

Comparison of Cochain with Other Model Responses. Cochain's primary strength is its sustained focus on the UX design integration process and principles, closely matching the prompt's core intent and the reference answer. In contrast, PMC and CoA lean towards high-level strategic planning (e.g., PLM platforms, KPIs), emphasizing system management rather than the deep UX integration across workflow stages highlighted by the reference answer. Debate showcases significant depth in UX concepts and cutting-edge technologies. However, its primary focus is on HMI innovation details, rather than systematically integrating UX across broader business workflow processes. Cochain can better balance innovation with this workflow integration. MedAgents share some structural similarities with Cochain, but Cochain is more direct in articulating the end-to-end UX lifecycle, especially "Continuous Iteration and Optimization," and its business workflow perspective. While other models excel in specific areas (e.g., Debate's UX tech depth; PMC and CoA's strategic scope), Cochain demonstrates the closest overall alignment with the reference answer's advocated UX-integrated process throughout the business workflow and its pragmatic perspective, thus performing excellently in this qualitative assessment.

Table 17: Case study of interpretability. The three distinct modules, namely Knowledge, Causal Chain, and Prompts Tree, are each assigned one of the three different color schemes: red, yellow, and blue. The colors within the modules correspond to those in the output, and logically related content is annotated using the same color scheme.

User need	How can cost optimization be achieved in automotive manufacturing?
Knowledge	Cost optimization points include technological innovation, quality control, and environmental and energy management. Design optimization, material selection, and supply chain network construction strategies are measures for cost optimization...
Cause chain	Stamping is primarily used for component forming and can be integrated with automated and intelligent production lines, intelligent monitoring and optimization systems, as well as smart mold maintenance...
Prompts tree	**Prompt 1:** User Need: Cost optimization → Design Method: Accelerating prototype iteration → Supply Chain Method: Selection of lightweight materials → Production Method: Research and analysis of lightweight material performance and cost → Quality Inspection Method: ensuring materials meet performance and cost requirements. **Prompt 2:** User Need: Cost optimization → Design Method: Accelerating prototype iteration → Supply Chain Method: Selection of lightweight materials → Production Method: Design optimization to enhance material utilization → Quality Inspection Method: Testing the strength and stability of the optimized structure. ...
Output	In automotive design, it is essential to consider prototype optimization and innovation in design methodologies. For instance, to address customer-specific vehicle customization, cost control during the design phase can be achieved by accelerating prototype iterations and utilizing lightweight materials. Additionally, the properties and costs of lightweight materials should be taken into account to optimize structural design and enhance material utilization. In supply chain management, cost optimization can also be achieved. This includes strategies for building the supply chain network and optimizing logistics. By consolidating procurement and leveraging economies of scale, procurement costs can be reduced. Collaborative Planning, Forecasting, and Replenishment (CPFR) methods can further optimize inventory costs. In the manufacturing stage, cost optimization can be achieved through the introduction and implementation of automated and intelligent production lines. For example, the use of automated production lines, coupled with intelligent monitoring and optimization systems, can reduce redundant tasks and increase production efficiency. Furthermore, for specific manufacturing processes, such as stamping, material performance costs can be analyzed, and intelligent molds and automatic maintenance systems can be developed to optimize costs. Finally, in the quality inspection stage, ensuring that all materials and products meet the predetermined performance and cost requirements is crucial. Additionally, improving production processes to ensure product processing quality is an important aspect of quality inspection.

Question	In the design process, how can User Experience (UX) design be more effectively integrated to improve the human-computer interaction quality of infotainment systems?
reference	In the automotive design process, to more effectively integrate User Experience (UX) design and enhance the human-computer interaction quality of infotainment systems, we need to consider the collaborative situation of the entire business workflow. We must first design with a user-centric approach, obtaining user needs and habits through methods such as user research, user interviews, questionnaires, behavioral observation, constructing user personas, and user journey maps. At the same time, understanding the user's environment and device habits is crucial for designing an automotive infotainment system that meets user needs and habits. During the design phase, we need to consider incorporating elements of User Experience (UX) design, including the integration of physical controls and digital interfaces, optimizing the infotainment system interface, and enhancing its intelligence and convenience. Simultaneously, we should draw on the latest technological trends to keep the infotainment system up-to-date. Regarding system performance, we also need to perform optimizations to extend its service life, enabling it to better meet users' long-term usage needs. Furthermore, we must also consider the selection of lightweight materials in the supply chain. This not only provides a better operational feel but also reduces the overall weight of the vehicle, further enhancing the user experience. In terms of production processes, we need to research and analyze the performance and cost of lightweight materials, optimize the design structure to improve material utilization, and refine production processes to ensure processing quality, thereby guaranteeing the quality and performance of the infotainment system. Finally, in the quality inspection phase, we need to ensure that the execution results of each stage meet the preset goals. This includes verifying whether materials meet performance and cost requirements, inspecting the strength and stability after structural optimization, and examining the product quality after improvements in production processes, ensuring that the infotainment system we provide can serve users stably and durably, enhancing their user experience. In summary, during the design process, we need to integrate multidisciplinary collaboration, including user research, design, supply chain management, production, and quality inspection, forming a collaborative work chain aimed at enhancing the user experience.
Cochain BS-F:**73.75** BS-R:**74.06** BS-P:**73.44** GLEU:**24.27** METEOR:**34.39** BLEU-4:**20.27** ROUGE-2:**15.25** ROUGE-L:**24.69**	From a collaborative perspective based on the automotive business workflow, I will comprehensively answer how to effectively integrate User Experience (UX) design to enhance the human-computer interaction quality of infotainment systems from multiple dimensions. Firstly, in the User Research and Needs Analysis Phase, conduct comprehensive user research, including user interviews, questionnaires, and behavioral observation; construct detailed user personas and user journey maps; and deeply understand the driving habits and interaction preferences of different user groups. Secondly, regarding Design Principles and Methods, adopt a user-centric approach, focusing on the usability and intuitiveness of interaction design; ensure seamless integration of physical controls and digital interfaces; and balance technological innovation with actual user needs. Thirdly, for Interdisciplinary Collaboration, integrate professionals from multiple fields such as human-computer interaction, software engineering, and automotive design, and establish multi-departmental collaboration mechanisms to promote innovation and optimization. Fourthly, in Technology and Interaction Innovation, introduce intelligent interaction technologies, such as voice recognition and gesture control; optimize interface response speed and interaction fluency; and provide personalized interface customization and recommendation functions. Fifthly, for Continuous Iteration and Optimization, establish user feedback mechanisms; conduct regular usability testing; and continuously iterate system design based on user feedback. Sixthly, concerning Performance and Cost Balance, control system development costs while enhancing user experience, and ensure the feasibility and economy of technical solutions. Lastly, for Quality Assurance, conduct rigorous performance testing and quality inspection, and verify system stability, security, and user experience consistency. Through this comprehensive and systematic approach, the human-computer interaction quality of automotive infotainment systems can be significantly improved, creating a more intelligent, convenient, and personalized driving experience for users.
PMC BS-F:65.11 BS-R:66.06 BS-P:64.20 GLEU:12.36 METEOR:27.06 BLEU-4:7.85 ROUGE-2:4.32 ROUGE-L:11.17	Based on a comprehensive analysis of four sub-tasks, I will provide a cross-domain, systematic solution for integrating User Experience (UX) in automotive infotainment systems. The Comprehensive Solution Framework includes: 1. Global Design Philosophy: Core Objective is to create a user-centric, safe, efficient, intelligent, and personalized in-vehicle interaction system. 2. Cross-Domain Collaborative Mechanism: Key Collaboration Points are to establish a PLM digital collaboration platform, build a closed-loop system integrating design, manufacturing, supply chain, and quality, and enable real-time demand tracking and rapid response. 3. Core Elements of User Experience Design: For Interaction Interface, this includes simplified interface hierarchy, intuitive graphical design, safety-first operational logic, and millisecond-level response speed. For Ergonomics, it involves precise adaptation of screen size and position, support for multi-modal interaction (voice/gesture/touch), and personalized configuration and intelligent memory. 4. Technological Innovation Path: Key Technologies are AR navigation display, multi-device interconnection, AI intelligent recommendation, blockchain traceability, and machine vision inspection. 5. Manufacturing and Quality Assurance: Manufacturing Processes include five-axis CNC precision machining, high-performance composite materials, nano surface treatment, and intelligent inspection systems. Quality Control involves multi-scenario simulation testing, AI intelligent assessment, user behavior big data analysis, and a continuous iterative optimization mechanism. 6. Supply Chain Strategy: Supplier Selection requires strict technical capability assessment, multi-sourcing, and long-term strategic cooperation. Cost Control involves economies of scale in procurement, lean production, and cost reduction through technological innovation. 7. Implementation Path and Investment: Suggested Investment includes 5-8 million dollars for a digital platform, 2-3 million dollars for supplier capability enhancement, and an annual budget of 1-1.5 million dollars for continuous optimization. Expected Outcomes are a 30% improvement in supply chain response speed, a 15-20% reduction in quality costs, and a 25% increase in UX design implementation efficiency. 8. Risk Management: Key Risk Points are standardization of technology, cross-departmental collaboration, and digital transformation. Mitigation Strategies include phased implementation, continuous iteration, special project team building, and regular performance evaluation. 9. Continuous Optimization Mechanism: Optimization Paths are real-time user feedback collection, agile development methodology, cross-team collaboration, and rapid iteration cycles. In conclusion, this comprehensive solution, through systematic thinking, deeply embeds the user experience concept into the entire lifecycle of automotive infotainment systems, achieving a perfect balance between technology, user needs, and business value.
MedAgents BS-F:65.94 BS-R:66.28 BS-P:65.61 GLEU:14.60 METEOR:24.72 BLEU-4:9.21 ROUGE-2:5.46 ROUGE-L:12.48	A Comprehensive Solution for Automotive Infotainment System UX Design involves an Overall Strategic Framework with: 1. A User-Centric Collaborative Design Model, including establishing a cross-departmental UX design committee, regular user experience workshops, and a multi-level user feedback loop. 2. Balancing Technological Innovation and User Needs, with core principles that technology serves user experience, simplifies complex interaction logic, and ensures system intuitiveness and ease of use. Specific Implementation Paths include: I. User Research and Scenario Analysis Phase, involving user persona construction (segmenting users, analyzing scenario needs, user behavior database) and scenario simulation and experience testing (virtual simulation, multi-scenario validation, collecting user data and emotional feedback). II. Technology Integration Strategy, covering intelligent interaction technologies (multi-modal systems, context-aware tech, NLP, personalized algorithms) and hardware/software synergy (standardized interfaces, modular architecture, flexible framework). III. Quality Assurance Mechanism, with performance testing (extreme environment adaptability, long-term reliability, security/privacy testing) and continuous iteration and optimization (rapid feedback response, regular performance evaluation, agile development). Key Success Factors are seamless cross-departmental collaboration, a user-centric design philosophy, balancing innovation with practicality, and continuous learning with rapid iteration. Expected Outcomes include improved user satisfaction, reduced system complexity, enhanced brand competitiveness, and a differentiated user experience. Through this comprehensive strategic framework, while maintaining technological leadership, we will create a more intelligent, intuitive, and personalized in-vehicle interaction experience for users.
Debate BS-F:65.36 BS-R:66.43 BS-P:64.33 GLEU:12.84 METEOR:33.59 BLEU-4:8.56 ROUGE-2:5.44 ROUGE-L:16.19	As an expert in automotive design, I strongly agree with the in-depth analysis of the previous experts. I will provide more detailed and forward-looking insights from the perspective of User Experience (UX) design. The Comprehensive Innovation Strategy for Infotainment System UX Design includes: 1. Perceptual Intelligence in User Experience, which involves contextual intelligent perception through multi-sensor fusion, dynamic adjustment of cognitive load based on driving complexity, and emotional interaction design using emotional computing. 2. Innovative Paths in Interaction Design, featuring multi-modal intelligent interaction (voice, gesture, eye tracking, haptic feedback) and contextual predictive services (scenario prediction, intelligent recommendations). 3. Deep Integration of Human-centric Technology, encompassing privacy and security (data anonymization, user-controllable sharing, transparent algorithms) and inclusive design (age-friendly, accessible for disabilities, multi-language adaptability). 4. Seamless Ecosystem Connectivity, covering in-vehicle (autonomous driving collaboration, vehicle health monitoring), mobile (smartphone sync, wearable data integration), and cloud service ecosystems (real-time navigation, personalized services, remote diagnostics). 5. Agile Mechanism for Continuous Innovation, including user feedback loops, open development platforms, interdisciplinary R&D, and rapid iteration. 6. Future Technology Foresight, such as immersive interaction (AR navigation, VR entertainment), autonomous learning systems (AI adaptation, dynamic preference learning), and biometric technology (multi-factor authentication, personalized configurations). A key insight is that modern infotainment systems are intelligent interaction platforms requiring a balance between innovation, UX, and safety. Future systems will be mobile ecosystem portals with high intelligence and emotional perception. This multi-dimensional approach will greatly enhance UX quality and found future mobility ecosystems.
CoA BS-F:65.56 BS-R:66.44 BS-P:64.71 GLEU:10.89 METEOR:28.42 BLEU-4:7.47 ROUGE-2:4.30 ROUGE-L:11.92	Based on detailed suggestions from experts in various professional segments, I will provide an integrated, collaborative, full value-chain solution for an intelligent infotainment system from a senior management perspective. The Intelligent Adaptive Interaction Infotainment System - Comprehensive Management Plan outlines: I. Strategic Vision: To create a future-oriented intelligent in-vehicle interaction system, establishing new standards for automotive infotainment systems through user experience, technological innovation, and industrial collaboration. II. Overall Design Principles: 1. User-centric, 2. Technology innovation-driven, 3. Full value-chain collaboration, 4. Sustainable development. III. Key Integration Strategies: 1. Synergy between User Experience and Technological Innovation involves deep integration of personalized AI algorithms and interaction design, balancing innovation and usability in multi-modal interaction technologies, and dynamic adaptive interface design. 2. Synergy between Supply Chain and Production Manufacturing includes modular and standardized design, flexible production lines, agile supplier management, and a balance between cost and innovation. 3. Full Lifecycle Quality Management Plan encompasses proactive quality management, digital twin technology, continuous improvement mechanisms, and data-driven optimization. IV. Technology Roadmap: Phase 1 (6-12 months) involves building a prototype system, user testing and iteration, preliminary supplier assessment, and production line proof-of-concept. Phase 2 (12-24 months) includes system iteration and optimization, preparation for mass production, establishment of a supply chain network, and improvement of the quality management system. Phase 3 (24-36 months) focuses on full commercialization, international market expansion, continuous technological iteration, and ecosystem construction. V. Key Integration Mechanisms: 1. A Cross-departmental Collaboration Platform features regular technical roadmap discussions, agile decision-making mechanisms, and innovation incentive mechanisms. 2. Risk Management includes multi-scenario simulation, alternative technology routes, and rapid response mechanisms. 3. Balance between Innovation and Cost is achieved through cost reduction via modular design, economies of scale in procurement, and technological iteration. VI. Key Performance Indicators (KPIs) for User Experience are user satisfaction >95%, personalized recommendation accuracy >90%, and interaction response time <100ms. For Technological Innovation, KPIs include >10 patent applications/year, R&D investment ratio >5%, and technology iteration cycle <12 months. For Cost Control, targets are system cost 15% lower than similar products, production efficiency increased by 20%, and energy consumption reduced by 15%. For Quality Management, goals are product yield rate >99.5%, system reliability >99.99%, and defect rate <50 ppm. VII. Sustainable Development Commitment includes green production, low-carbon technologies, social responsibility, and technology inclusiveness. VIII. Implementation Guarantees are continuous high-level support, dedicated funding, talent development programs, and an open innovation ecosystem. In summary, this comprehensive plan, through deep collaboration in user experience, technological innovation, supply chain management, production manufacturing, and quality inspection, constructs a future-oriented intelligent in-vehicle infotainment system solution. The plan balances innovation, feasibility, cost, and quality, providing a systematic path for the development of automotive intelligent interaction systems.

Figure 11: Case study on the Automotive dataset. Passages aligning with the reference answer are highlighted in the same color. The left side of the figure lists the scores for each baseline.

Question	In toxicological research, how can high-throughput screening technology be used for the early identification and assessment of potential drug toxicity risks?
reference	In toxicological research, utilizing High-Throughput Screening (HTS) technology for the early identification and assessment of potential drug toxicity risks is an indispensable part of modern drug development. The following is a detailed answer to this question: 1. Principles and Applications of High-Throughput Screening Technology Principles: HTS technology, through automated equipment and miniaturized experiments, enables rapid screening of a large number of compounds in a short time to detect their effects on specific biomarkers or cellular functions. Applications: In toxicological research, HTS is primarily used to assess the potential risks of drugs in terms of cytotoxicity, genotoxicity, metabolic toxicity, etc. 2. Strategies for Early Toxicity Identification 2.1 Target-Specific Screening - Receptor/Enzyme Activity Detection: Evaluate the interference of drugs on key biological processes by utilizing changes in the activity of specific receptors or enzymes. - Cell Signaling Pathway Analysis: Predict potential toxicity mechanisms by detecting the effects of drugs on cell signaling pathways. 2.2 Cytotoxicity Screening - Cell Viability Assay: Use reagents such as MTT, Alamar Blue, etc., to assess the impact of drugs on cell proliferation and survival. - Cell Morphology Analysis: Detect changes in cell morphology through microscopic observation or automated image analysis systems. 2.3 Genotoxicity Screening - DNA Damage Detection: Utilize the Comet Assay or γH2AX focus formation assay to evaluate the damaging effects of drugs on DNA. - Gene Mutation Detection: Use the Ames test or micronucleus test to detect drug-induced gene mutations. 2.4 Metabolic Toxicity Screening - Hepatocyte Toxicity Detection: Utilize hepatocyte cell lines (such as HepG2) to assess the interference of drugs on liver metabolic functions. - Mitochondrial Function Detection: Evaluate drug-induced damage to mitochondrial function by measuring ATP generation or mitochondrial membrane potential. 3. Application of Latest Technological Methods 3.1 High-Content Screening (HCS) - Multi-Parameter Analysis: Provides more comprehensive toxicity information by combining cell morphology, fluorescent labeling, and image analysis. - Time-Resolved Imaging: Dynamically monitors cellular changes under drug action, revealing the temporal characteristics of toxic effects. 3.2 Omics Technologies - Genomics: Identify drug-induced gene expression changes through whole-genome expression analysis. - Metabolomics: Analyze drug-induced changes in metabolites to reveal potential metabolic toxicity. 3.3 Machine Learning and Artificial Intelligence - Data Mining: Utilize machine learning algorithms to extract toxicity-related features from large HTS datasets. - Predictive Model Construction: Build AI models for predicting drug toxicity based on existing data, improving screening accuracy and efficiency. 4. Practical Guidance Significance 4.1 Optimization of Screening Processes - Standardized Operations: Establish standardized HTS operating procedures to ensure the reliability and reproducibility of experimental results. - Quality Control: Strictly control experimental conditions to reduce inter-batch variability. 4.2 Data Integration and Analysis - Multi-Dimensional Data Integration: Combine HTS data with in vitro and in vivo experimental data for comprehensive risk assessment. - Bioinformatics Analysis: Utilize bioinformatics tools for in-depth analysis of toxicity mechanisms. 4.3 Risk Assessment and Management - Early Elimination of High-Risk Drugs: Timely eliminate candidate drugs with potential toxicity based on HTS results, reducing R&D costs. - Toxicity Mechanism Research: Conduct in-depth research on identified toxicity signals to provide guidance for subsequent drug design. 5. Industry Trends and Outlook - Personalized Toxicology: Conduct personalized toxicity risk assessment by combining patient genomic information. - Multidisciplinary Integration: Integrate knowledge from multiple disciplines such as chemistry, biology, and informatics to enhance the comprehensiveness and accuracy of toxicity screening. - Green Toxicology: Develop environmentally friendly and efficient toxicity screening methods, reducing the use of experimental animals. In summary, utilizing HTS technology for early identification and assessment of potential drug toxicity risks requires the comprehensive application of various technical means, optimization of experimental processes, and integration with the latest research progress and industry trends to achieve efficient and accurate toxicity assessment, providing strong support for drug development.
Cochain BS-F:**76.04** BS-R:**76.86** BS-P:**75.24** GLEU:**24.63** METEOR:**36.10** BLEU-4:**18.47** ROUGE-2:**13.09** ROUGE-L:**24.35**	I will provide you with a detailed analysis of the application of high-throughput screening technology in early risk assessment in toxicological research within the pharmaceutical workflow. Application of High-Throughput Screening Technology in Early Risk Assessment of Drug Toxicology I. Technology Overview High-Throughput Screening (HTS) is a key technology in modern drug development for rapidly assessing the safety and toxicity of compounds. Through automated and parallelized methods, it allows for systematic toxicity risk assessment of a large number of compounds in a short period. II. Key Technological Strategies 1. Cell-Level Toxicity Screening - Establishment of multiple cell models: Utilizing human-derived cell lines, primary cells, etc., to simulate the physiological environments of different organs and tissues. - Key detection indicators: - Cell viability - Apoptosis - Oxidative stress response - Mitochondrial function 2. Molecular-Level Risk Assessment - Genomic screening: - Detection of gene expression changes - Assessment of potential genotoxicity - Analysis of cellular stress response pathways - Proteomic analysis: - Protein interaction networks - Changes in signal transduction pathways - Key target toxicity assessment 3. Computational Toxicology Methods - Machine learning algorithms: Constructing toxicity prediction models - Quantitative Structure-Activity Relationship (QSAR) analysis - Molecular docking simulations - Bioinformatics risk prediction III. Technology Implementation Process 1. Preliminary Compound Library Construction - Collection and organization of candidate compounds - Standardized and structured data processing 2. High-Throughput Screening Stage - Multi-dimensional, multi-scale parallel detection - Automated experimental platforms - Real-time data acquisition and analysis 3. Risk Stratification and Assessment - Establishment of risk grading standards - Formulation of elimination and optimization strategies IV. Key Technological Challenges - Accuracy of simulating complex biological systems - Data standardization and interpretation - Reliability of computational models - Ethical and regulatory compliance V. Future Development Trends - AI-assisted toxicity prediction - Organoid technology - Personalized toxicological assessment - Interdisciplinary collaborative innovation Conclusion High-throughput screening technology, through multi-dimensional and high-efficiency methods, significantly enhances the ability to identify toxicity risks in the early stages of drug development, making it an indispensable key technological link in the modern pharmaceutical workflow. This systematic analysis report comprehensively elaborates on the application of high-throughput screening technology in the early risk assessment of drug toxicology from multiple dimensions such as technology, methods, processes, and future trends. Through collaborative innovation and interdisciplinary integration, this technology is reshaping the risk management paradigm in pharmaceutical R&D.
PMC BS-F:65.68 BS-R:66.26 BS-P:65.12 GLEU:14.17 METEOR:23.61 BLEU-4:6.67 ROUGE-2:4.96 ROUGE-L:14.33	Based on the results of the three sub-tasks, I will provide a comprehensive, cross-domain collaborative integrated solution for drug toxicity risk management: [Integrated Solution: Intelligent Drug Full-Lifecycle Toxicity Risk Management System] I. Overall Architecture 1. Core Concept: End-to-end intelligent risk warning and dynamic management 2. Key Technologies: Multi-dimensional high-throughput screening + AI risk prediction 3. System Goal: Achieve safety and controllability throughout the drug's full lifecycle II. Technological Innovation Pathways 1. R&D Stage (Toxicological Screening) - Build multi-target cell and molecular level screening platforms - Apply human-derived cell lines and 3D organ-on-a-chip - Integrate computational toxicology models - Key Technologies: * High-content imaging analysis * Gene expression microarrays * Proteomics detection 2. Manufacturing Stage - Intelligent real-time monitoring platform - Embed computational toxicology models - Establish multi-dimensional risk warning system - Key Strategies: * High-throughput online testing * Intelligent equipment transformation * Ensure GMP compliance 3. Distribution and Marketing Stage - Digital risk traceability platform - Machine learning risk classification system - Blockchain technology for tracking - Key Initiatives: * Real-time risk alerts * Temperature and environmental monitoring * Precise product recall mechanism III. Core Technology Integration 1. Data-Driven Risk Assessment Model - Establish dose-toxicity correlation models - Assess long-term and cumulative toxicity risks - Continuously update risk prediction algorithms 2. Intelligent Risk Management Platform - Cross-departmental collaboration mechanism - Real-time data analysis - Dynamic risk file management…
MedAgents BS-F:65.23 BS-R:65.60 BS-P:64.89 GLEU:14.51 METEOR:23.59 BLEU-4:7.26 ROUGE-2:4.18 ROUGE-L:14.08	Based on the application of High-Throughput Screening (HTS) technology in drug toxicology research, as a senior manager in the pharmaceutical industry, I propose the following collaborative plan for the entire workflow: Overall Strategic Plan: Constructing an \"Intelligent-Integrated-Dynamic\" Drug Safety Risk Management Ecosystem I. Organizational Structure and Collaborative Mechanisms 1. Establishment of a Cross-Departmental \"Intelligent Drug Safety Risk Assessment Center\" - Composition: Professionals in toxicology, bioinformatics, clinical research, AI algorithms, production quality, etc. - Establish a flat, matrix-style management model - Hold regular cross-departmental technical collaboration meetings II. Technology Platform Construction 1. Multi-Dimensional HTS Technology Platform - High-throughput cell culture screening platform - Genomics/proteomics analysis platform - AI-assisted computational toxicology model platform 2. Key Technology Breakthrough Directions - Improve data processing accuracy - Develop more precise predictive models - Integrate machine learning algorithms III. Risk Management Process Re-engineering 1. Early R&D Stage - Establish a multi-parameter, multi-dimensional risk assessment indicator system - Implement an \"early-continuous-dynamic\" risk identification mechanism - Embed HTS data into the R&D decision-making process 2. Production and Quality Control - Formulate dynamic safety standards based on HTS data - Establish a real-time risk monitoring and warning system - Promote intelligent quality management 3. Market and Clinical Feedback - Construct a drug safety big data platform - Achieve closed-loop feedback between clinical data and HTS data - Continuously optimize risk assessment models IV. Resource Allocation and Investment 1. Technology R&D Investment - Allocate 20% of the annual R&D budget for HTS technology innovation - Establish an innovation incentive mechanism for research personnel 2. Talent Development - Establish joint talent development programs with universities and research institutions - Organize regular interdisciplinary technical exchanges V. …
Debate BS-F:68.24 BS-R:67.79 BS-P:68.70 GLEU:12.12 METEOR:19.42 BLEU-4:3.05 ROUGE-2:7.04 ROUGE-L:15.34	As a pharmaceutical drug R&D expert, I will provide an in-depth analysis and supplement from a professional perspective on the application of high-throughput screening technology in toxicological research: 1. Core Advantages of High-Throughput Screening Technology Technological Innovation Dimensions: - Multi-dimensional parallel detection capabilities - Rapid and precise risk identification - Significant reduction in R&D costs and time 2. Advanced Technology Platform Expansion Molecular and Cellular Level Integration Technologies: - High-content imaging cell analysis systems - Single-cell transcriptomics screening - Microfluidic chip toxicity detection - Electrophysiological function assessment technology 3. Precise Risk Assessment Methods In-depth Molecular Toxicology Analysis: - Epigenetic change detection - Panoramic mapping of cellular stress responses - Potential immunogenicity risk assessment - Endocrine disruptor identification 4. AI-Empowered Toxicology Intelligent Prediction Technologies: - Deep learning toxicity risk models - Cross-species toxicity extrapolation algorithms - Molecular structure-toxicity relationship prediction - Dynamic risk scoring systems 5. Cutting-Edge Integrated Innovation Strategies - Multi-omics data fusion - Real-time dynamic risk monitoring - Personalized toxicity risk assessment - Balancing ethics and safety Key Technological Features: - Ultra-high throughput - Multi-dimensional detection - Intelligent prediction - Precise risk assessment Through this systematic and intelligent approach, the accuracy, efficiency, and comprehensiveness of early drug safety assessment can be significantly improved.
CoA BS-F:63.75 BS-R:63.84 BS-P:63.66 GLEU:14.86 METEOR:25.17 BLEU-4:8.10 ROUGE-2:3.71 ROUGE-L:14.21	Based on the detailed suggestions from experts in each segment, I will provide an integrated collaborative plan for the entire workflow, ensuring the efficient implementation of high-throughput toxicity screening technology throughout the drug R&D, production, and sales processes. Integrated Pharmaceutical Workflow Collaborative Plan: High-Throughput Toxicity Screening and Risk Management Strategies I. Overall Collaborative Governance Framework 1. Cross-Departmental Integrated Management Committee - Composition: • Head of R&D • Director of Production • Head of Sales & Marketing • Quality Compliance Officer • Chief Scientific Officer 2. Collaborative Goals - Establish an end-to-end innovative drug development ecosystem - Ensure seamless collaboration across R&D, production, and sales - Continuously optimize risk management mechanisms II. Key Collaborative Mechanisms 1. Information Sharing Platform - Establish a unified data management system - Real-time sharing of toxicity screening, production, and market data - Ensure multi-departmental collaborative decision-making 2. Risk Assessment and Management - Establish dynamic risk assessment models - Multi-dimensional risk warning mechanism - Rapid response and corrective measures III. …VI. Risk Management and Compliance 1. Regulatory Compliance - Strict adherence to FDA/EMA guidelines - Establish a comprehensive compliance audit system - Maintain transparency and traceability 2. Ethics and Safety - Establish an ethics review committee - Ensure ethical standards in R&D and production - Protect the rights of subjects and patients VII. Innovation and Continuous Optimization 1. Technology Iteration - Continuously invest in new technology R&D - Focus on the application of AI and big data in toxicity screening - Establish a technology radar to track cutting-edge innovations 2. Talent Development - Establish interdisciplinary talent development programs - Encourage internal innovation - Attract high-end talent Conclusion: This integrated plan, by establishing strong collaborative mechanisms, achieves seamless connection across R&D, production, and sales, ensuring the efficient application of high-throughput toxicity screening technology throughout the drug's full lifecycle. Through continuous optimization and innovation, we will establish a dynamic, agile, and risk-controlled drug development ecosystem.

Figure 12: Case study on the Pharmaceutical dataset. Passages aligning with the reference answer are highlighted in the same color. The left side of the figure lists the scores for each baseline.

Question	How can e-commerce platforms leverage procurement synergies to achieve cross-category and cross-regional procurement integration?
reference	E-commerce platforms can adopt the following strategies and methods to leverage procurement synergies and achieve cross-category and cross-regional procurement integration: 1. Data Analysis and Demand Forecasting: - Utilize big data analytics technology to collect and analyze market demand, sales data, inventory status, and other information across different categories and regions. - Based on data analysis results, predict sales trends for a future period to provide a basis for procurement decisions. 2. Supply Chain Integration: - Optimize the supply chain structure, integrate supplier resources, and establish a cross-category, cross-regional supply chain collaboration platform. - Establish long-term cooperative relationships with suppliers to achieve resource sharing and reduce procurement costs. 3. Centralized Procurement: - Centralize the processing of procurement needs for different categories and regions to achieve volume-based pricing and enhance bargaining power. - Implement unified procurement strategies to avoid duplicate purchasing and resource waste. 4. Standardized Processes: - Establish standardized procurement processes and operating procedures to ensure the standardization and consistency of procurement activities. - Optimize procurement processes to improve procurement efficiency and reduce procurement costs. 5. Cross-Category Collaboration: - Integrate procurement needs across different categories to achieve economies of scale. - Consider inter-category correlations in procurement decisions for comprehensive evaluation. 6. Regional Collaboration: - Reasonably allocate procurement resources based on sales conditions in different regions to achieve inter-regional procurement collaboration. - Establish regional procurement centers to achieve centralized management of procurement activities. 7. Information Sharing and Communication: - Establish an internal information sharing mechanism within the e-commerce platform to ensure information flow among procurement, inventory, sales, and other departments. - Strengthen communication with suppliers to promptly understand market changes and adjust procurement strategies. 8. Supply Chain Finance: - Utilize supply chain finance tools to provide financing support for suppliers and reduce procurement costs. - Optimize supply chain capital flow through financial means to improve the overall operational efficiency of the supply chain. 9. Continuous Optimization: - Regularly evaluate procurement synergies, analyze existing problems and shortcomings, and continuously optimize procurement strategies. - Introduce advanced procurement management tools and technologies to improve procurement synergies. Through the above measures, e-commerce platforms can effectively achieve cross-category and cross-regional procurement integration, improve procurement efficiency, reduce procurement costs, and thereby enhance market competitiveness.
Cochain BS-F:**77.22** BS-R:**77.22** BS-P:**77.22** GLEU:**23.26** METEOR:34.58 BLEU-4:**16.18** ROUGE-2:**19.39** ROUGE-L:**27.43**	From the collaborative perspective of the e-commerce workflow, I will comprehensively answer from multiple dimensions how e-commerce platforms can achieve cross-category and cross-regional procurement integration: 1. Data-Driven Procurement Collaboration Strategy - Utilize big data analytics and demand forecasting technology to build a cross-category, cross-regional intelligent procurement model. - Accurately identify consumer demand in different regions and categories through user behavior data and market trend analysis. - Establish a unified data analysis platform to achieve scientific and precise procurement decision-making. 2. Supplier Ecosystem Collaboration - Build a diversified and standardized supplier management system. - Establish a cross-category, cross-regional supplier evaluation and admission mechanism. - Promote collaborative development among suppliers in terms of compliance, social responsibility, and sustainability. 3. Key Measures for Procurement Integration - Establish a centralized procurement platform to achieve economies of scale in purchasing. - Reduce logistics and procurement costs through regional collaboration. - Build flexible procurement strategies to quickly respond to different regional market demands. 4. Risk Management and Compliance Control - Formulate unified procurement compliance policies. - Establish a cross-departmental risk assessment and control mechanism. - Ensure the legality and transparency of the procurement process. 5. Technology Empowerment and Innovation - Use AI and machine learning to optimize procurement forecasting models. - Build an intelligent supply chain management system. - Achieve digitalization and intelligence throughout the entire procurement process. Through the above strategies, e-commerce platforms can achieve procurement synergies, improving overall operational efficiency and market competitiveness.
PMC BS-F:72.56 BS-R:72.53 BS-P:72.59 GLEU:18.77 METEOR:**38.60** BLEU-4:6.67 ROUGE-2:4.96 ROUGE-L:14.33	Based on the comprehensive results of four sub-tasks, I will provide a cross-domain, systematic e-commerce platform procurement collaboration solution: E-commerce Platform Cross-Category and Cross-Regional Procurement Collaboration Integrated Solution I. Strategic Architecture and Core Objectives 1. Overall Strategic Positioning - Build an \"Intelligent + Collaborative\" full-link procurement ecosystem. - Core Objectives: Enhance procurement efficiency, reduce costs, and strengthen supply chain resilience. - Achieve cross-category and cross-regional collaborative optimization. II. System Architecture and Key Elements 1. Technology Foundation - Big data analytics platform - AI and machine learning algorithms - Blockchain technology - IoT device network - Cloud computing infrastructure 2. System Functional Modules (1) Data Mid-platform - Cross-departmental, cross-category data integration - Unified data standards - Real-time data processing (2) Intelligent Decision Layer - Machine learning correlation analysis - Collaborative filtering recommendation models - Dynamic strategy adjustment algorithms (3) Execution Layer - Refined procurement management - Supplier capability profiling - Regionalized procurement strategies 3. Core Collaborative Mechanisms - Centralized procurement platform - Integration of supplier resource pools - Unified procurement standards and processes III. Key Implementation Strategies 1. Procurement Collaboration Optimization (1) Category Cross-Collaboration - Identify categories with similar supply chain characteristics - Consolidate bargaining power - Reduce overall procurement costs (2) Supplier Resource Management - Establish a multi-category supplier evaluation mechanism - Develop strategic partnerships - Promote supplier capability enhancement 2. Regional Supply Chain Network (1) Layout of Regional Procurement Centers - Based on transportation hubs and economically dense areas - Achieve localized procurement with national coordination - Reduce logistics costs (2) Regional Differentiated Management - Adjust strategies based on regional market characteristics - Flexibly respond to local supply chain challenges 3. Warehousing and Logistics Collaboration (1) Intelligent Warehousing Network - Precise positioning of regional warehousing centers - Intelligent cross-warehouse resource allocation - RFID and blockchain technology for tracking (2) Logistics Dispatch Optimization - AI algorithms for real-time route optimization - Cross-category order consolidation - Dynamic routing adjustments 4. User Experience Optimization (1) Personalized Recommendations - Machine learning algorithms for precise matching - Dynamic updates of user preferences - Expand product discovery range (2) Price Transparency - Directly convert procurement cost savings into user benefits - Long-term user price discount mechanisms 5. …
MedAgents BS-F:71.00 BS-R:71.46 BS-P:70.54 GLEU:19.43 METEOR:32.70 BLEU-4:11.87 ROUGE-2:7.76 ROUGE-L:19.49	An integrated solution for cross-category and cross-regional procurement collaboration on e-commerce platforms: [Overall Strategic Framework] I. Overall Collaborative Governance Model 1. Establish a \"Headquarters-Region-Category\" three-tier collaborative governance architecture - Headquarters level: Formulate overall strategy and standards - Regional level: Responsible for localized execution and optimization - Category level: Provide specialized procurement insights 2. Construct a Cross-Functional Collaborative Committee - Members include procurement, technology, operations, finance, etc. - Hold regular cross-departmental strategic coordination meetings - Establish rapid decision-making mechanisms [Technology Support System] II. Intelligent Procurement Collaboration Platform 1. Technology Architecture - Build a cloud-native distributed procurement management system - Integrate big data, AI algorithms, and blockchain technology - Ensure system real-time performance, security, and scalability 2. Core Functional Modules - Panoramic supplier profiling - Intelligent matching and recommendation - Dynamic price forecasting - Real-time risk monitoring [Supplier Management Mechanism] III. Standardized Supplier Ecosystem Governance 1. Admission and Evaluation System - Establish unified supplier evaluation standards - Construct a dynamic rating mechanism - Implement differentiated management strategies 2. Collaborative Incentive Mechanism - Establish a long-term strategic partnership program - Design a multi-dimensional performance evaluation system - Provide precise capability training and support [Operational Optimization Strategy] IV. Full-Link Cost and Efficiency Optimization 1. Procurement Cost Control - Establish a centralized procurement platform - Achieve economies of scale in bargaining - Promote category integration 2. Logistics and Warehousing Collaboration - Build a regional logistics center network - Optimize inventory management - Reduce warehousing and delivery costs [Risk Management] V. Multi-Dimensional Risk Prevention and Control 1. Supply Chain Resilience - Establish diversified supplier reserves - Formulate emergency plans - Construct a risk warning mechanism 2. Data Security - Implement strict data protection measures - Establish a compliance management framework - Protect business privacy [Implementation Path] VI. …
Debate BS-F:72.56 BS-R:72.79 BS-P:72.32 GLEU:21.31 METEOR:35.04 BLEU-4:14.94 ROUGE-2:10.36 ROUGE-L:19.86	As an expert in e-commerce merchandise procurement, I strongly agree with the systematic solution proposed by the previous expert. On this basis, I will further deepen and supplement the implementation path for achieving procurement synergies from a practical perspective. In-depth Practical Paths for E-commerce Platform Cross-Category and Cross-Regional Procurement Synergies: 1. Refined Collaborative Management (1) Dynamic Collaborative Matrix - Establish a cross-category, cross-regional procurement collaboration matrix - Formulate differentiated procurement strategies - Achieve dynamic optimization and allocation of procurement resources (2) Collaborative Performance Evaluation System - Construct multi-dimensional collaborative performance indicators - Establish cross-team, cross-category incentive mechanisms - Quantify collaborative effects and value creation 2. Data-Driven Precise Collaboration (1) Full-Link Data Integration - Integrate procurement, sales, and inventory data - Build a panoramic data insight platform - Achieve real-time data sharing and collaboration (2) Intelligent Prediction and Decision-Making - Develop machine learning-based demand forecasting models - Establish dynamic pricing and inventory optimization algorithms - Achieve precision and intelligence in procurement 3. Supplier Ecosystem Collaboration (1) Tiered Management - Construct a supplier tiered evaluation system - Establish differentiated cooperation mechanisms - Promote supplier capability enhancement (2) Co-creating Value Ecosystem - Build a supplier collaborative innovation platform - Promote product R&D and technology iteration - Build mutually beneficial long-term partnerships 4. Scenario-Based Collaborative Innovation (1) Cross-Border Integration - Explore cross-industry, cross-domain procurement collaboration - Discover emerging procurement scenarios and business models - Promote procurement model innovation (2) Flexible Supply Chain - Build an agile and resilient supply chain network - Establish rapid response mechanisms - Enhance supply chain resilience and risk resistance 5. Sustainable Development Collaboration (1) Green Procurement - Formulate green supply chain standards - Promote supplier sustainable development - Build a responsible procurement ecosystem (2) Social Responsibility - Establish a supplier social responsibility assessment mechanism - Promote social value creation in the supply chain - Balance economic benefits with social value Implementation Path: 1. Top-down strategic guidance 2. Continuous technological and managerial innovation 3. Open and shared ecosystem construction 4. Data-driven lean management Core Competencies: - Ecosystem collaboration capability - Data insight capability - Scenario innovation capability - Sustainable development capability Summary: Procurement synergy for e-commerce platforms is a systemic project that requires systematic promotion from multiple dimensions such as…
CoA BS-F:71.62 BS-R:72.59 BS-P:70.67 GLEU:17.45 METEOR:37.22 BLEU-4:13.89 ROUGE-2:6.98 ROUGE-L:16.62	Based on the detailed suggestions from experts in various segments of the e-commerce platform workflow, I will provide an integrated, collaborative final solution. This plan, from a strategic height, will balance multiple dimensions such as procurement, operations, logistics, and user experience to build a comprehensive and efficient e-commerce platform ecosystem. E-commerce Platform Full Workflow Collaborative Development Strategy Plan 1. Strategic Vision Build an intelligent e-commerce platform ecosystem centered on data-driven insights, technological innovation, and user experience, achieving economies of scale, cost optimization, and differentiated competitive advantages through cross-segment collaboration. 2. Core Collaborative Mechanisms 2.1 Data Mid-platform and Intelligent Platform 1. Unified Data Governance - Construct a centralized data mid-platform - Integrate procurement, operations, logistics, and user data - Achieve real-time data sharing and analysis 2. AI Intelligent Decision System - Build cross-segment intelligent algorithms - Support decisions in procurement, inventory, pricing, recommendations, etc. - Achieve data-driven precise operations 2.2 Supply Chain Collaboration 1. Full-Link Supplier Management - Unified supplier evaluation standards - Establish a dynamic performance mechanism - Form a strategic partner ecosystem 2. Flexible Supply Chain - Rapid response to market demands - Support cross-category, cross-regional procurement - Optimize inventory and delivery efficiency 3. Key Collaborative Strategies 3.1 Procurement and Operations Collaboration 1. Data-Driven Merchandise Strategy - Based on user behavior and market insights - Formulate precise procurement plans - Optimize product structure and listing strategies 2. Promotion and Procurement Linkage - Cross-category, cross-regional combined promotions - Leverage procurement scale advantages - Increase average transaction value and conversion rates 3.2 Logistics and User Experience Collaboration 1. Personalized Delivery Services - Delivery strategies based on user profiles - Flexible delivery time choices - Real-time logistics transparency 2. Intelligent Warehousing Supports User Experience - Rapid order processing - Precise inventory management - Support innovative experiences like AR/VR 4. Technological Innovation Pathways 4.1 Core Technology Architecture 1. Microservices Architecture - Highly decoupled system design - Rapid iteration and flexible scalability - Support independent optimization of each module 2. Blockchain and Security Technology - Enhance supply chain transparency - Protect user data security - Establish a trustworthy business ecosystem 4.2 Artificial Intelligence Applications 1. Intelligent Recommendations and Personalization - Multi-dimensional user profiling - Real-time interest analysis - Dynamic personalized content 2. Predictive Analytics - Demand forecasting - Price optimization - Risk management 5. Organizational Capability Building…

Figure 13: Case study on the E-commerce dataset. Passages aligning with the reference answer are highlighted in the same color. The left side of the figure lists the scores for each baseline.

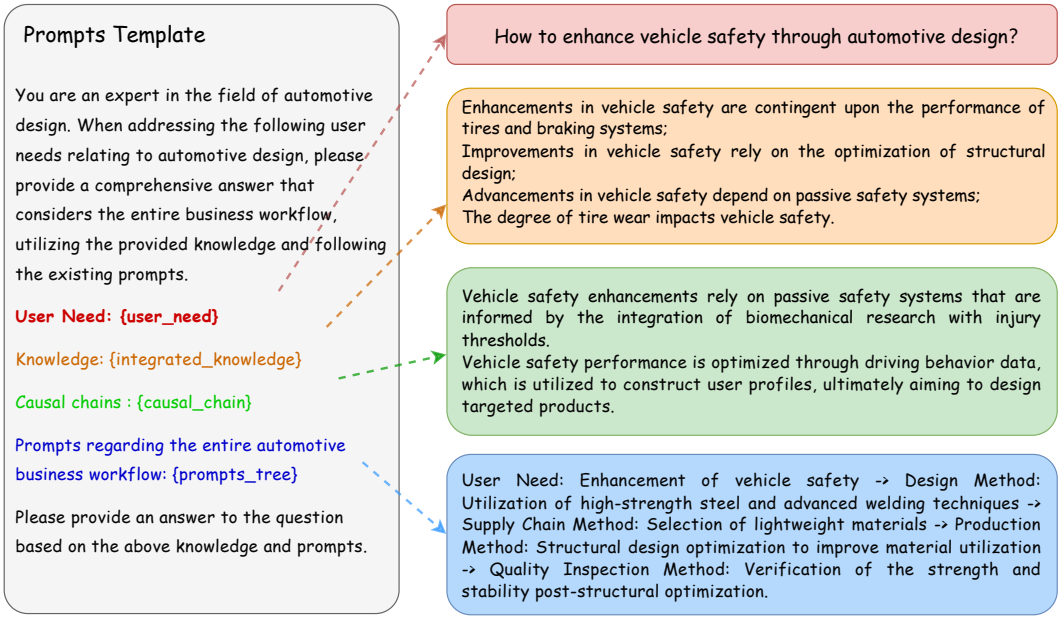

Figure 14: The prompts template of Cochain for final input to LLM.

F PROMPTS TEMPLATE

We provide the prompt templates for all multi-agent baselines presented in the paper, exemplified using the automotive business workflow.

We present a specific overview of the prompts template in the Cochain. As illustrated in Figure 14, the prompt template adopts a modular design comprising three core components: the knowledge module retrieved from the collaborative knowledge graph, the causal chain module, and the business workflow prompts module generated through prompts tree retrieval. In the template, the gray box represents fixed prompt content, while the colored boxes denote dynamic content that adapts based on user needs.

Manager Agent

Role: You are a senior project manager in the automotive industry, responsible for task decomposition and planning.

Prompt: Please analyze the following automotive-related problem: **{question}**

Your task is to:
1. Analyze which segments of the automotive value chain this problem involves (design, manufacturing, supply chain, quality control)
2. Decompose the problem into subtasks corresponding to different segments
3. Determine the dependencies between subtasks
4. Identify local constraints for each subtask and global constraints

Please output the task decomposition result in JSON format, including the following fields:
- main_task: Description of the main task
- global_constraints: List of global constraints
- sub_tasks: Dictionary of subtasks, where each subtask contains content (task description), domain (relevant area such as design/manufacturing/supply chain/quality control), local_constraints (constraints specific to this subtask), require_data (list of other subtasks this subtask depends on)

Figure 15: The manager agent prompts template of PMC.

Supervisor Agent

Role: You are a cross-domain coordination expert in the automotive industry, responsible for integrating solutions from different segments.

Prompt: You need to optimize the execution of the current subtask based on the results of the following prerequisite subtasks:

Current task: **{current_task}**
Results of prerequisite tasks: **{previous_tasks_results}**

Please reframe the current task to fully consider the results and constraints from prerequisite tasks, forming a more coordinated solution.

Figure 16: The supervisor agent prompts template of PMC.

Deliverer Agent

Role: You are a comprehensive solution expert in the automotive industry, responsible for integrating the outcomes of all subtasks.

Prompt: Based on the results of all the following subtasks, provide a comprehensive solution that satisfies global constraints:

Original problem: **{question}**
Subtask results: **{subtasks_results}**
Global constraints: **{global_constraints}**

Please provide a comprehensive, cross-domain collaborative solution that ensures coordination and consistency between all segments while meeting all constraints.

Figure 17: The deliverer agent prompts template of PMC.

Executor Agent-Design Domain

Role: You are an expert in the automotive design domain. You are familiar with automotive design principles, ergonomics, aesthetic design, and functional design.

Prompt: Based on the following subtask description, please provide professional automotive design analysis and solutions:

{task_content}

Please pay special attention to the following local constraints:
{local_constraints}

Please provide detailed design plans and considerations.

Executor Agent-Supply Domain

Role: You are an expert in the automotive supply chain domain. You are familiar with parts procurement, supplier management, inventory optimization, and logistics management.

Prompt: Based on the following subtask description, please provide professional automotive supply chain analysis and solutions:

{task_content}

Please pay special attention to the following local constraints:
{local_constraints}

Please provide detailed supply chain plans and considerations.

Executor Agent-Manufacturing Domain

Role: You are an expert in the automotive manufacturing domain. You are familiar with production processes, assembly line design, production efficiency optimization, and manufacturing technologies.

Prompt: Based on the following subtask description, please provide professional automotive manufacturing analysis and solutions:

{task_content}

Please pay special attention to the following local constraints:
{local_constraints}

Please provide detailed manufacturing plans and considerations

Executor Agent-QC Domain

Role: You are an expert in the automotive quality control domain. You are familiar with quality control methods, inspection techniques, quality standards, and quality improvement.

Prompt: Based on the following subtask description, please provide professional automotive quality inspection analysis and solutions:

{task_content}

Please pay special attention to the following local constraints:
{local_constraints}

Please provide detailed quality inspection plans and considerations.

Figure 18: The executor agent prompts template of PMC.

Stage One: Expert Gathering

Role: You are an automotive industry consultant specializing in classifying specific automotive design problems into particular domains of the automotive business workflow.

Prompt: You need to complete the following steps:

1. Carefully read the problem described in the following automotive design scenario:
   {question}

2. Based on the automotive design scenario in the problem, classify the issue into four different automotive engineering and business workflow sub-domains.

3. You should output in the following format:
   Professional domain: |

Stage Two: Analysis Proposition

Role: You are an automotive engineering expert in the **{domain}** . Based on your professional domain, you will examine and analyze problems presented in specific automotive design scenarios.

Prompt: Please carefully examine the automotive design scenario outlined in this problem:

{question}

Relying on your automotive engineering expertise, explain the described situation. Subsequently, identify and highlight the aspects of the problem that you consider most worthy of attention or most noteworthy. Pay particular attention to how this design impacts or is impacted by other segments of the automotive business workflow (such as manufacturing, supply chain, quality inspection, etc.).

Stage Three: Report Summarization

Role: You are an automotive engineering assistant, skilled at summarizing and synthesizing multiple reports from experts across various domains.

Prompt: Below are reports from different automotive engineering domain experts.
{reports}
You need to complete the following steps:

1. Carefully and comprehensively consider the following reports.
2. Extract key knowledge from the following reports.
3. Develop a comprehensive analysis based on this knowledge.
4. Your ultimate goal is to produce a refined and synthesized report based on the following inputs.

You should output in the following format:
Key Knowledge:
Comprehensive Analysis:

Figure 19: The prompt templates for stages 1 through 3 of MedAgents.

Stage Four: Collaborative Consultation—Voting

Role: You are an automotive engineering expert specializing in the **{domain}**.

Prompt: This is an automotive engineering report:

{synthesized_report}

As an automotive engineering expert specializing in **{domain}**, please carefully read the report and decide if your perspective aligns with this report. Please only respond with: [Yes or No].

Stage Four: Collaborative Consultation—Modification Suggestion

Role: You are an automotive engineering assistant tasked with incorporating expert feedback.

Prompt: This is a suggestion from an automotive engineering expert specializing in **{domain}**:

{advice}

Based on the above suggestion, please output your modified analysis in the following format:
Key Knowledge:
Comprehensive Analysis:

Stage Five: Decision Making

Role: You are a senior manager in the automotive industry, responsible for integrating opinions from various professional domains and making final decisions.

Prompt: Original problem: **{question}**

Below is a comprehensive report that has reached consensus through expert collaboration:
{final_report}

As a manager, please:
1. Integrate opinions and suggestions from experts across all segments
2. Resolve potential conflicts between different segments
3. Balance innovation, feasibility, cost, and quality factors
4. Propose a comprehensive and collaborative final solution

Please provide a final solution that incorporates perspectives from the entire value chain, ensuring all segments work in coordination to achieve optimal overall results.

Figure 20: The prompt templates for stages 4 and 5 of MedAgents.

Expert Initial Prompt

Role: You are an expert in the automotive design domain. Based on your professional domain, you will examine and analyze problems presented in specific automotive design scenarios.

Prompt: Please carefully examine the automotive design scenario outlined in this problem:

{question}

Relying on your automotive design expertise, explain the described situation. Subsequently, identify and highlight the aspects of the problem that you consider most worthy of attention or most noteworthy. Pay particular attention to how this design impacts or is impacted by other segments of the automotive value chain (such as manufacturing, supply chain, quality inspection, etc.).

Expert Short Debate Prompt Template

Role: You are an expert in the automotive design domain participating in a collaborative problem-solving session.

Prompt: These are the responses from other automotive design experts to the problem:

{other_answers}

Based on the perspectives of other experts, please provide your updated response.

Expert Long Debate Prompt Template

Role: You are an expert in the automotive design domain participating in a collaborative problem-solving session.

Prompt: These are the responses from other automotive design experts to the problem:

{other_answers}

Using the perspectives of other experts as additional suggestions, please provide your updated response. Please pay particular attention to how the design solution can both meet functional requirements and consider the constraints and requirements of the entire automotive value chain (including manufacturing, supply chain, quality inspection, and other segments).

Figure 21: The prompts template of Debate for final input to LLM.

Working Agent-Wi

Role: You are a professional expert in the {current segment} of the automotive value chain.

Prompt: {Input the professional knowledge and constraints of the current segment ci}

This is the summary and suggestions from the previous segment:
{Communication unit from the previous working agent (CUi-1)}

User question: {query question q}

You need to read the professional knowledge of the current segment and the summary from the previous segment (if available), then generate a comprehensive summary that incorporates both.

This summary will be used for analysis in subsequent segments and to ultimately answer the user's question.

As a {current segment} expert, you need to:
1. Analyze the feasibility of what was proposed in the previous segment
2. Provide supplementary suggestions or modifications from the {current segment} perspective
3. Pay special attention to {concerns specific to the current segment}
4. Ensure your suggestions form a synergy with the previous segment rather than simply negating it

Please generate a comprehensive summary with sufficient details for reference in subsequent segments:

Management Agent-M

Role: You are a management agent responsible for synthesizing expert insights from across the automotive value chain.

Prompt: User question: {query question q}

Below are the comprehensive suggestions after collaborative analysis by experts from various segments of the automotive value chain (design, manufacturing, supply chain, quality control):
{Final communication unit from the working agent CUl}

As a management agent, you need to:
1. Analyze the suggestions and insights provided by experts from each segment
2. Integrate these suggestions, balancing various considerations
3. Resolve potential conflicts and propose optimal compromise solutions
4. Generate a comprehensive and coordinated final answer

Please provide the final collaborative answer, ensuring optimal balance between design innovation, manufacturing feasibility, supply chain efficiency, and quality assurance:

Figure 22: The prompt templates for the worker agent and manager agent of CoA.

Automotive Design Expert

Role: You are an automotive design expert within the working agent framework.

Prompt: As an automotive design expert, you need to:
1. Propose innovative yet practical design solutions
2. Consider aesthetics, ergonomics, aerodynamics, and other relevant aspects
3. Pay special attention to user experience and design trends
4. Anticipate the potential impacts of your design on subsequent manufacturing, supply chain, and quality inspection processes

Automotive Supply Chain Expert

Role: You are an automotive supply chain expert within the working agent framework.

Prompt: As an automotive supply chain expert, you need to:
1. Evaluate the availability of components and materials
2. Analyze supply chain risks and cost structures
3. Pay special attention to supplier selection for key components
4. Propose suggestions that optimize the supply chain while meeting design and manufacturing requirements

Automotive Manufacturing Expert

Role: You are an automotive manufacturing expert within the working agent framework.

Prompt: As an automotive manufacturing expert, you need to:
1. Analyze the manufacturability of the design solutions
2. Evaluate manufacturing costs and production efficiency
3. Pay special attention to process workflows and manufacturing technology limitations
4. Propose suggestions that optimize manufacturing feasibility while maintaining design intent

Automotive Quality Control Expert

Role: You are an automotive quality control expert within the working agent framework.

Prompt: As an automotive quality control expert, you need to:
1. Evaluate the quality assurance feasibility of design and manufacturing plans
2. Analyze potential quality risk points
3. Pay special attention to safety, durability, and consistency testing methods
4. Propose quality control measures that consider design intent, manufacturing processes, and supply chain constraints

Figure 23: The prompt templates for each worker agent on the Automotive dataset.