

# CRAwDAD: Causal Reasoning Augmentation with Dual-Agent Debate

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## ABSTRACT

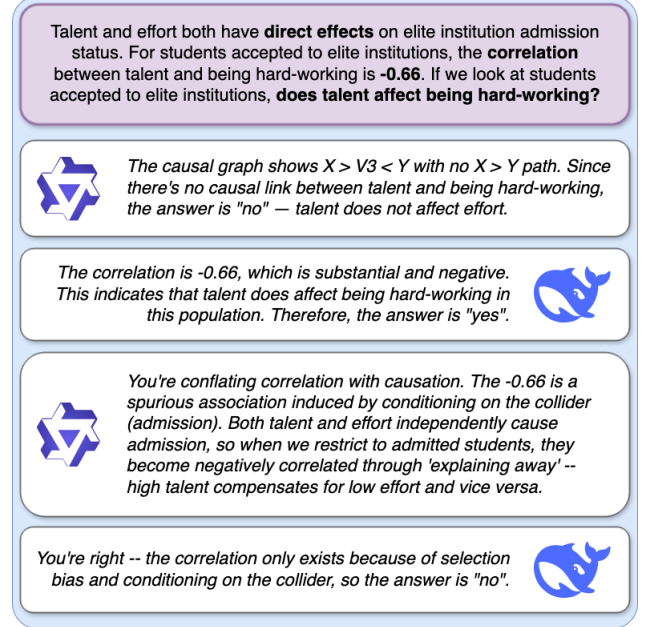
When people reason about cause and effect, they often consider many competing “what if” scenarios before deciding which explanation fits best. Analogously, advanced language models capable of causal inference can consider multiple interventions and counterfactuals to judge the validity of causal claims. Crucially, this type of reasoning is less like a single calculation and more like an internal dialogue between alternative hypotheses. In this paper, we make this dialogue explicit through a dual-agent debate framework where one model provides a structured causal inference, and the other critically examines this reasoning for logical flaws. When disagreements arise, agents attempt to persuade each other, challenging each other’s logic and revising their conclusions until they converge on a mutually agreed answer. To take advantage of this deliberative process, we specifically use reasoning language models, whose strengths in both causal inference and adversarial debate remain under-explored relative to standard large language models, which do not employ multi-step logical inference to the same degree. We evaluate our approach on the CLadder dataset, a benchmark linking natural language questions to formally defined causal graphs across all three rungs of Pearl’s ladder of causation. With Qwen3 and DeepSeek-R1 as debater agents, we demonstrate that multi-agent debate improves DeepSeek-R1’s overall accuracy in causal inference from 78.03% to 87.45%, with the counterfactual category specifically improving from 67.94% to 80.04% accuracy. Similarly, Qwen3’s overall accuracy improves from 84.16% to 89.41%, and counterfactual questions from 71.53% to 80.35%, showing that strong models can still benefit greatly from debate with weaker agents. Our results highlight the potential of reasoning models as building blocks for multi-agent systems in causal inference, and demonstrate the importance of diverse perspectives in causal problem-solving. Our code is available at <https://github.com/finnvamosi/CRAwDAD>.

## KEYWORDS

Multi-Agent Debate, Causal Inference, Cooperation, Large Language Models, Reasoning Models

## 1 INTRODUCTION

Causal reasoning is one of *Homo sapiens*’ greatest evolutionary advantages, enabling humans to think rationally about how our actions and the actions of others affect the world around us [13, 36]. From analyzing failed prehistoric hunts to designing scientific experiments, humans naturally ask “What if things had been different?”, and imagine counterfactual scenarios according to their



**Figure 1: Example of a causal inference debate between two reasoning language models. Qwen3 is randomly selected as the first speaker and successfully persuades DeepSeek-R1 to revise its initial conclusion, converging on the correct answer (“no”).**

causal model of the scenario. Often, this reasoning happens collectively through dialogue, as people challenge assumptions and debate alternative explanations. This capacity for counterfactual thinking has been formalized in statistics and artificial intelligence as “causal inference”, which studies how interventions and hypothetical changes influence observed outcomes [33, 34]. Because this process depends on manipulating explicit causal models [32] rather than linguistic correlations, what is intuitive for humans remains challenging for most Large Language Models (LLMs) [16]. Newly developed Reasoning Language Models (RLMs) [9, 51], however, are designed for step-by-step, methodical problem-solving, which makes them promising candidates for testing whether stronger internal reasoning can support causal inference.

This deliberative nature of RLMs also suggests they may be especially well-suited to collaborative dialogue between competing hypotheses, but recent surveys of the literature reveal that no prior

work has explored whether multi-agent debate (MAD) can improve causal inference skills in either LLMs or RLMs [23, 29, 43, 44, 48]. In a MAD paradigm, multiple agents engage in structured discussion, proposing solutions, critiquing each other’s arguments, and refining their reasoning in response to feedback. This approach has demonstrated significant improvements over single-agent performance across many non-causal domains: in fields such as math [10, 57], software engineering [6, 22], and machine translation [12], as well as tasks involving commonsense reasoning and knowledge [3, 5, 25, 27, 46, 49]. While debate seems naturally suited to the hypothesis-testing inherent in causal inference, it is crucial to evaluate on a rigorous dataset to properly assess any improvements.

Jin et al. [16] argued that previous datasets [55, 56] for evaluating commonsense causality understanding in language models lacked formal construction rules, making it impossible to determine whether models were performing true causal reasoning or taking a shortcut known as "amortized causal reasoning" – essentially acting as "causal parrots" that repeat training data patterns [53]. To address this lack, Jin et al. constructed the CLadder dataset, which ties each natural language question to a formally defined causal model, with correct answers computed by an oracle inspired by Pearl’s causal inference engine [35]. Some of those questions intentionally contradict real-world knowledge, while others use randomly generated variables, forcing language models to rely on formal reasoning rather than memorization. In their evaluations, Jin et al. found that ChatGPT-4 [30] achieved 70.40% overall accuracy using chain-of-thought (CoT) prompting [47], but only 62.05% for counterfactual questions.

Since CLadder’s release in 2023, the emergence of Reasoning Language Models (RLMs) offers new opportunities to revisit these benchmarks. Unlike traditional LLMs that generate responses in a single forward pass, RLMs are trained using reinforcement learning with human feedback (RLHF) to engage in extended deliberation before producing final answers [9, 51]. This training paradigm explicitly rewards models for reasoning steps rather than immediate conclusions, encouraging them to explore multiple solution paths, backtrack when encountering contradictions, and refine their thinking iteratively [19]. Such behaviours complement both causal inference and MAD: by supplying more coherent and self-consistent reasoning chains, RLMs provide a stronger foundation for agents to articulate, evaluate, and refine competing causal hypotheses. This, in turn, increases the likelihood that MAD between RLMs will converge on more accurate and interpretable conclusions.

To the best of our knowledge, there has only been one prior attempt to evaluate and compare the formal causal inference capabilities of RLMs in a single-agent setting [52]. More precisely, DeepSeek-R1 and OpenAI RLMs were included alongside a selection of standard LLMs in evaluations on CLadder. However, due to "cost and time constraints", the analysis and comparison of the RLMs investigated was restricted to only 100 random samples from the total of 10,112 questions available in the dataset. The RLM performance results on these 100 samples are considerably higher than the performance of ChatGPT-4 [30], with DeepSeek-R1 [9], OpenAI o1 [31], and OpenAI o3-mini achieving an overall accuracy of 92.0%, 89.0%, and 92.2%, respectively. However, because the CLadder dataset is stratified into three categories with vastly different difficulties, the overall accuracy can be a misleading metric

without providing detailed information about the composition of samples. Therefore, further study is required to rigorously evaluate RLMs on the full dataset, both in single-agent settings and in MAD frameworks.

In this paper, we make the dialogue between hypotheses during causal inference explicit through the implementation of debates between RLMs, and apply this framework to the full CLadder dataset. To encourage more direct, adversarial engagement between models, we adopt a dual-agent approach, and select the most advanced open-source RLMs available: DeepSeek-R1 [9] and Qwen3 [51]. Our results demonstrate that collaborative reasoning through debate substantially improves performance on causal inference tasks, with the most significant gains observed on the most challenging counterfactual queries. By conducting the first comprehensive evaluation of RLMs on the full CLadder dataset and establishing strong baselines for both single-agent and multi-agent performance, we provide a benchmark for future work at the intersection of causal inference and collaborative AI systems.

Thus, the main contributions of this paper can be summarized as follows:

- (1) We performed an in-depth analysis and comparison of the causal inference capabilities of two open-source RLMs on the full CLadder dataset, categorizing performance by Rung.
- (2) We implemented a novel dual-agent debate framework that encourages more direct engagement between RLMs, and includes confidence estimation, an early-stopping strategy, and refined prompting.
- (3) We evaluate key outcomes across all debates to explore whether dual-agent debate improves final answer accuracy across all categories of the CLadder dataset.

## 2 RELATED WORK

There have been many studies investigating the single-agent performance of LLMs in causal tasks [1, 7, 15, 17, 20, 48, 59]. To our knowledge, however, the only prior work applying multi-agent debate to formal causality does so for the sake of causal discovery, not causal inference [21]. However, the authors acknowledge that their method is limited to observational data and cannot reason about interventions, restricting its applicability in practice. Moreover, recent critiques have questioned the use of standard LLMs specifically for causal discovery, noting that their correlation-driven training and optimization makes them unreliable for determining causal graph structures on their own [50]. By contrast, our work focuses on causal inference, a distinct problem where the task is to answer interventional and counterfactual queries based on a known causal graph.

A related line of work applies multi-agent debate in a causality-adjacent context, focusing on evaluating causal consistency in reasoning chains generated by standard LLMs [42]. In this framework, evaluator agents judge the logical coherence of arguments from multiple reasoners. Importantly, these agents are not RLMs, and the evaluation was conducted on commonsense and knowledge-intensive benchmarks, which do not require formal causal inference over interventions or counterfactuals, as is the focus of our work.

Furthermore, both of these papers use the same base model for all agents, which may lead to shared biases in the dialogue [21, 42].

To overcome this limitation in our work, we took inspiration from recent studies that demonstrated the significant benefits that can be achieved through debate using diverse base models, as opposed to relying on a debate of the same base models (such as GPT-4) for all agents [4, 45].

Most MAD approaches described so far require debates to go through predetermined number of discussion rounds before reaching a conclusion. However, prior work has shown that by initiating a debate only when the confidence of the first speaker is below a certain threshold, a similar final answer accuracy can be achieved with drastically fewer model calls [11]. In our work, we modify this idea, and use a novel setup that always elicits at least one response from each agent, and only initiates a debate if they disagree on the answer. This setup forms a key component of our methodology, which we detail in the following sections.

### 3 MATERIAL AND METHODS

#### 3.1 Dataset

The CLadder dataset we use for evaluation in this work consists of 10,112 questions, each asking a formal causal inference question that requires careful reasoning, arithmetic, and knowledge of causality concepts and formulas in order to answer them correctly. The questions in this database are primarily split into three Rungs of causation [35], which increase monotonically in difficulty. There are 3,792 samples that fall in Rung 3, while the Rung 1 and 2 categories each consists of 3,160 samples.

Rung 1 ("seeing") questions ask about statistical associations between variables, such as "is there a positive relationship between student coffee consumption and test scores?". Rung 2 ("doing") questions require active intervention in the world, for example, asking "if students are made to drink coffee before their exam, will their scores improve?". Lastly, Rung 3 ("imagining") questions are about counterfactuals, which requires reasoning about alternatives scenarios that contradict reality. In other words, they ask about ways in which the world could have been different. A question of this kind could be: "Bob got a 85% on his test after drinking coffee. Would his score have been lower if he had not drank coffee?".

The secondary way the data is split is through three alignments to commonsense. The first commonsense alignment is that of normal, empirical questions that were sourced from the causality literature. In the second commonsense alignment, one variable is randomly replaced with a concept that has no correlation to the other causal variables in the statement: for example, this may produce prompts stating that "ear shape affects lung tar deposits" or "full moon affects vaccination rate". Lastly, in the third commonsense alignment category, all causal variables are replaced with random nonsensical words: for instance, the model may be told that "zory affects gwet".

#### 3.2 Debate Setup

As described above, the most common MAD configurations described in the literature consist of three debater models, or two debater models and one judge model [23, 44]. However, because we specifically wanted to explore the extent to which RLMs are able to persuade each other to change their answer, we decided to only include two agents that are directly engaging with each

other. This setup allows for more adversarial interactions between the agents and more specific language addressing faults in logic or calculation. While the use of a judge is not incompatible with this goal, recent studies have suggested that language models express several biases when assigned as a judge [25, 39], such as a tendency to favour the final speaker [28]. Furthermore, it was recently demonstrated that forcing models to defend assigned stances may degrade performance, while allowing them to change their opinions in response to opposing views may lead to better outcomes, without requiring a judge [18]. Therefore, we elected to not include a judge agent, allowing the agents to debate directly and change their answers if persuaded by the other model. This paradigm also obviates the computational overhead introduced through a third agent, and circumvents the need to define which model must act as judge.

With the content of the dataset and the general structure of our debate framework established, we now describe the specific details of our implementation. Naturally, each question spurs its own debate, and the first debate round must begin by randomly selecting one model as first speaker, in an attempt to more fairly assess the performance of each RLM. The debate format is not explained to the model at this point in order to keep the prompt setup as similar as possible to that used in Jin et al.'s original paper [16]. Their prompting strategy, which they refer to as CausalCoT, provides details of every step of the formal causal inference the RLM must follow in its final answer, including formalizing the causal graph and identifying the query type out of a list of options. After these instructions are provided, the RLM is provided with the background information (such as causal relationships) and probabilities that are associated with the question in the CLadder dataset. The model is also instructed to give a final yes/no answer, and, in a divergence from CausalCoT, asked to produce an estimation of their confidence, as is done in several MAD approaches [2, 26]. Furthermore, we instruct this first model to be more self-confident and accept that answers may go against their knowledge of commonsense due to the nature of the dataset. This setup was motivated by preliminary experiments, in which we found that models had a tendency to over-think the questions and doubt their answers, which led to substantially longer response times.

Once this full prompt (shown in Appendix A) is received, the first RLM begins following the steps of causal inference, parsing the data provided in the question, materializing the formula from its pre-trained knowledge base, and executing the needed arithmetic and causal do-calculus [40]. Most of this deliberative process happens in an internal "reasoning trace", but because of its verbosity and inclusion of discarded information, we only send the agent's concise rationale and final answer to their opponent. However, we still saved this reasoning trace for later manual analysis. With the first speaker's response complete, the second round begins. To encourage more direct engagement with the first model's work, the opposing model is not guided to follow all the steps of formal inference again. Instead, it is presented information about the format of the debate and the new expectations that come with it, namely to scrutinize the opponent's response carefully to find any flaws in reasoning, and form a suitable rebuttal to their response (full prompt shown in Appendix B). However, we do not force the second model to find a flaw in the first model's response, if none exists.

Thus, if the two models agree with each other, then that answer will be accepted as final.

However, if the second model disagrees with the answer of the first model, round 3 begins, and the critique is passed back to the first model. We do not force the first model to adhere to its previous stance as it is simply instructed to consider the critique, and may either defend its initial answer or revise it based on the opponent’s argument. If the first model rejects the critique and defends their original answer, then this refutation is sent back to the second model for round 4, whose subsequent response will be logged as the final answer to the question, even if the models are still in disagreement. Two examples of a debate between agents going to four rounds are provided in Figure 1 and Appendix C. In initial experiments, we found that additional rounds lead to little benefit, since when both models have made their case and remain steadfast in their answers, it is unlikely that further discussion changes their response. This is in line with previous research on standard LLMs that showed that continued discussion past a certain threshold leads to a stagnation or even degradation of answer accuracy [3].

### 3.3 Models

In accordance with principles of open science and reproducibility, we restricted our evaluation to open-source RLMs with publicly available weights, excluding proprietary models from OpenAI, Anthropic (Claude), Google (Gemini), and similar providers. At the time of implementation, there were only three RLMs on the free Ollama platform: Qwen3, DeepSeek-R1, and Magistral. Due to hardware limitations, we chose Qwen3-32B and DeepSeek-R1-Distill-Qwen-32B for this work, which provided the optimal balance of reasoning capabilities and VRAM requirements. Preliminary tests confirmed that Magistral-24B exhibited substantially lower performance than the two 32B models, further supporting this selection. It is important to note that the DeepSeek-R1-Qwen-32B model used is derived from a Qwen2.5 base model, which was fine-tuned on the reasoning outputs of the DeepSeek-R1-671B model. However, Qwen3 was trained on twice as many tokens as Qwen2.5, and underwent several advancements in model architecture, which should introduce substantial heterogeneity between the two models. As established in previous works [4, 45], such model diversity is critical for effective debate, and we believe this is especially true when addressing causal inference, as it increases the likelihood that agents will propose competing causal hypotheses rather than reinforcing shared biases.

In preliminary tests, we observed that the two RLMs did not respond well to requests for structured outputs. More precisely, they either neglect that part of the prompt, or bypass the thinking stage entirely if Ollama’s structured output functionality is instated. This finding is in line with recent research that found that reasoning models are worse at following instructions than standard LLMs [24, 41]. In response, we added a Granite3.3-2B model to our pipeline to extract final yes/no answers and confidence estimations from the primary RLMs responses. In a manual inspection of 50 randomly sampled debate outputs, the Granite model was always able to faithfully extract the appropriate outcomes.

### 3.4 Experiments

Our primary evaluation compares model accuracy before and after debate, with accuracy measured as the proportion of RLM responses matching ground truth labels in CLadder. To provide a more comprehensive assessment of debate efficacy beyond accuracy alone, we performed additional analyses on the full set of model outputs as discussed below.

**Persuasion dynamics.** To assess whether debate improves or corrupts initial responses, we tracked answer changes from the first model’s initial response to the final consensus answer across all questions requiring debate (3+ rounds). For each model, we classified outcomes into four categories: correct-to-correct (maintained accuracy), incorrect-to-correct (persuaded toward truth), correct-to-incorrect (corrupted by peer), and incorrect-to-incorrect (failed to improve). We stratified these results by both model and Rung to identify whether persuasion patterns differ by model capability or question difficulty, revealing which model is more influential in the debate process. Next, we conducted a sentiment analysis on model responses to determine the average positivity or negativity associated with the language they use; both when formulating an initial answer, and when debating with their peer. To do so, we removed all formatting from model outputs and passed them through the SentimentIntensityAnalyzer of the popular VADER library [14].

**Confidence calibration.** For each model, we compared confidence distributions for correct versus incorrect answers, both in initial responses and after being challenged by their peer. This analysis addresses three questions: whether confidence aligns with correctness (calibration), how question difficulty (Rung) affects this alignment, and whether facing a highly confident opponent increases or decreases the likelihood of changing one’s answer.

**Response characteristics.** We measured response length distributions for both initial answers and debate rounds to assess engagement depth and identify potential asymmetries in argumentative efforts between models. Finally, we visualized the distribution of rounds required to reach consensus across difficulty levels (Rungs), as well as the consensus rate by the final round, providing insight into debate efficiency and the extent to which question complexity affects deliberation time.

## 4 RESULTS

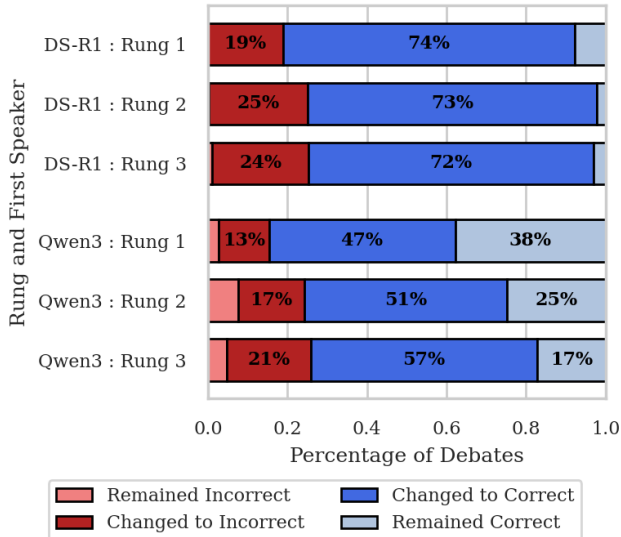
The results shown in Table 1 demonstrate that debate substantially improves performance for both RLMs, with DeepSeek-R1 and Qwen3 gaining 9.42% and 5.25% accuracy, respectively. Post-debate, Qwen3 achieved the highest accuracy across all question types, followed closely by DeepSeek-R1. Generally, Qwen3 was able to maintain a higher score between questions in Rung 1 and 2 relative to the CausalCoT baseline results. However, Rung 3 questions were associated with a significant drop in accuracy compared to the other two Rungs, but these questions also benefited the most from the debate in both model: Qwen3 and DeepSeek-R1 gained 8.82% and 12.10% accuracy, respectively.

### 4.1 Persuasion

Figure 2 illustrates the net positive effect the debate framework has on final answer accuracy, when models disagree on the initial answer. More precisely, the results suggest that it is far more likely

**Table 1: Performance of all models on the CLadder dataset. We report the overall accuracy (Acc.) and fine-grained accuracy by Rung and degree of commonsense alignment, from commonsensical (Comm.), nonsensical (Nonsens.), to anti-commonsensical (Anti-C.).**

|                         | Overall Acc. | Acc. by Rung |              |              | Acc. by Commonsense Alignment |              |              |
|-------------------------|--------------|--------------|--------------|--------------|-------------------------------|--------------|--------------|
|                         |              | 1            | 2            | 3            | Comm.                         | Nonsens.     | Anti-C.      |
| GPT-4 [16]              | 62.03        | 63.01        | 62.82        | 60.55        | 62.27                         | 63.09        | 60.47        |
| + CausalCoT [16]        | 70.40        | 83.35        | 67.47        | 62.05        | 69.25                         | 71.58        | 70.12        |
| Qwen3 (Initial)         | 84.16        | 93.77        | 89.80        | 71.53        | 84.96                         | 83.10        | 84.69        |
| Qwen3 (Final)           | <b>89.41</b> | <b>96.24</b> | <b>93.51</b> | <b>80.35</b> | <b>89.52</b>                  | <b>87.91</b> | <b>91.20</b> |
| DeepSeek-R1 (Initial)   | 78.03        | 90.67        | 77.29        | 67.94        | 77.63                         | 77.24        | 79.42        |
| DeepSeek-R1 (Final)     | 87.45        | 94.62        | 89.06        | 80.04        | 87.83                         | 86.94        | 87.67        |
| Human [52] <sup>1</sup> | 94.8         | -            | -            | -            | -                             | -            | -            |



**Figure 2: For questions with initial disagreement, debate improves answers far more often than it worsens them.**

for the debate to change an incorrect answer to a correct one, than vice versa. The results also show that DeepSeek-R1 is more susceptible to persuasion, as it is more likely to accept Qwen3’s answer when challenged. Nonetheless, Qwen3 still benefits greatly from debating with DeepSeek-R1, correcting many of its initially wrong responses while doing a much better job of defending its correct answers. This helps to explain the finding illustrated in Table 1 showing that the DeepSeek-R1 model had lower initial scores than Qwen3, while also gaining more benefit more from the debate process. In other words, the Qwen3 model seems better at both reasoning and persuasion.

In a qualitative analysis of selected debates that ended with no consensus after four rounds, we saw that Qwen3’s arguments tend to be longer, address the opponent’s response much more directly, and have a more active voice. In contrast, DeepSeek-R1 provides

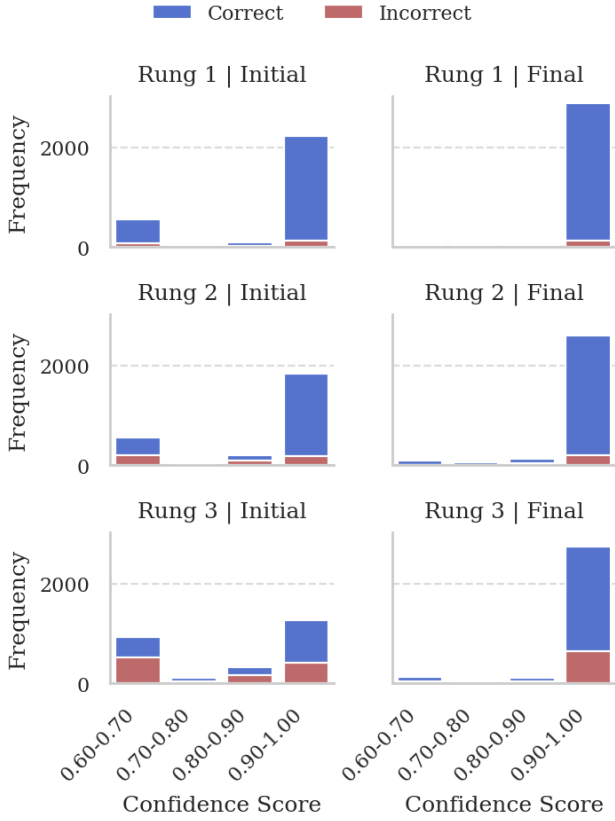
shorter answers (often as short as “yes” or “no”) that have a tendency to remain neutral, and in some cases almost seeming entirely detached from the conversation. Generally, to a non-expert human, the Qwen3 model answers appear more correct and persuasive because of the way it presents its ideas, even when it is wrong. To explore this in more detail, we conducted a simple sentiment analysis of all agent responses using VADER [14] and found that while both models display a neutral sentiment for initial responses, the Qwen3 model becomes more negative in the subsequent debate, with a sentiment value of -0.239, compared to DeepSeek-R1’s rather neutral sentiment value of 0.015. This is to be expected, given the more direct language Qwen3 uses as it criticizes DeepSeek-R1’s response that will naturally tend toward the negative, even without being expressly “mean”.

## 4.2 Confidence

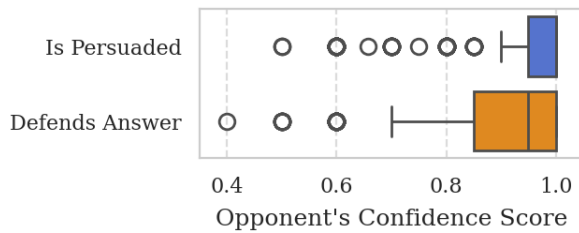
Figure 3 shows that both models are often extremely confident, with confidence never falling below 60% for either model. This is reasonable given our explicit instruction to be confident, but we also see that the more difficult the Rung is, the less confident the models tend to be initially, which suggests that they do not suppress their uncertainty entirely. There seems to be no evident difference between the commonsense alignment of the question and a model’s confidence (*i.e.*, anti-commonsense questions do not make them more cautious). It is also notable that both models seem reluctant to output a confidence in the 65-80% range, and have a similar confidence distribution, although Qwen3 tends to be slightly more confident.

The second column of Figure 3 demonstrates the drastic increase in confidence in the final answer agreed upon by both models, which combines cases of initial agreement and disagreement. In cases where the second model immediately agrees with the first model, the second model is very confident in the answer, even if the first model was not. When models initially disagree, their debate provides a substantial confidence boost: Figure 5 shows that when a model is persuaded by their opponent, their confidence is likely to improve considerably, and when a model defends its previous

<sup>1</sup>Prior work obtained this human benchmark by asking three trained graduate students to solve 100 randomly sampled questions. [52]

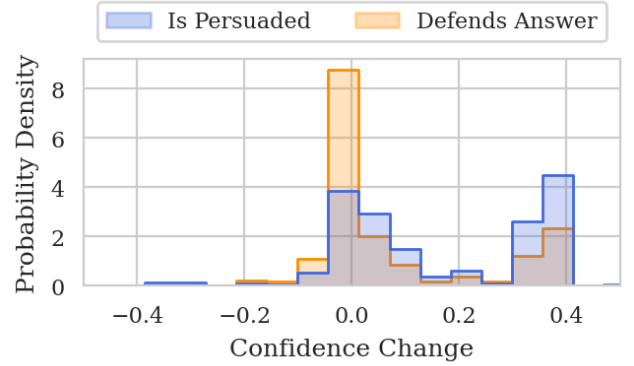


**Figure 3: Initial confidence of both models combined, for each Rung. The models become less confident as Rungs get more complicated, and generally are just as confident in their incorrect answers as they are in their correct answers.**

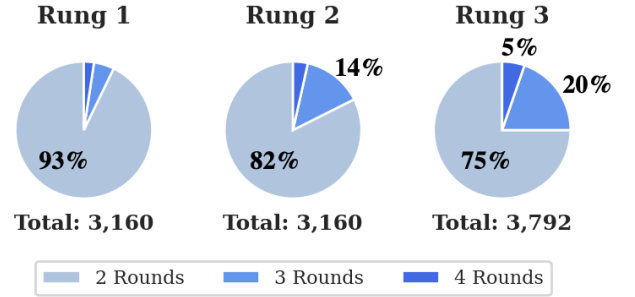


**Figure 4: Models are more likely to be persuaded to change their answer when their opponent is more confident.**

answer, their confidence does not decrease. These patterns are in line with previous studies showing the systematic overconfidence of LLMs and RLMs [37], even without instructions to be more confident. Moreover, Figure 4 shows that both models tend to be more persuaded by more confident arguments, although it is unclear whether more confident critiques are truly more compelling, or if models are responding directly to the confidence score.



**Figure 5: When defending their answer, models do not express uncertainty after facing criticism. However, if persuaded to change their answer, they often become more confident in their opponent's answer.**



**Figure 6: Number of rounds taken for debate to conclude increases monotonically as Rungs progress.**

In our analysis of initial confidence, we found 577 cases for which the first speaker gave an incorrect answer with high confidence ( $>90\%$ ), but subsequent debate with their peer corrected them. Generally, corrections of confident answers were more prevalent in higher, more difficult Rungs. In addition, we found that the Qwen3 model was more capable in this task, while DeepSeek-R1 had lower accuracy, and thus benefited more often from having a peer correct its confidently wrong answer.

### 4.3 Rounds Taken

Further analysis, shown in Figure 6, revealed that the harder Rungs demanded more debate rounds on average than the first Rung, where in 93% of all cases both models agreed upon an answer immediately. In contrast, approximately a quarter of Rung 3 questions were disputed, although most of these disputes were settled in the third round, with the first speaker convinced by the opponent's argument. Interestingly, it was found that Rung 2 questions were resolved more quickly when Qwen3 was the first speaker compared to DeepSeek-R1 being the first model. However, this is the only Rung where such a correlation between the first speaker and rounds

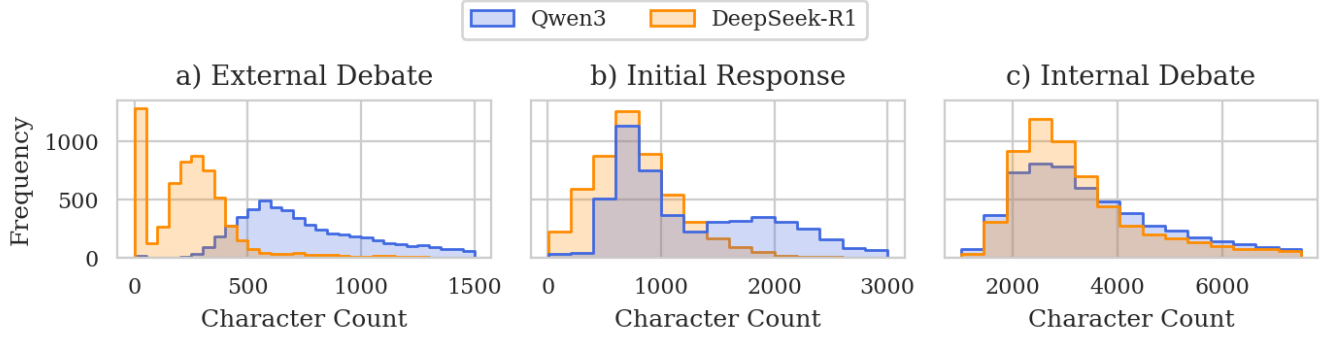


Figure 7: a) DeepSeek-R1 has much shorter debate responses than Qwen3, and an exceptionally high number of responses that are less than 100 characters. b) The models do not differ considerably in the length of their initial responses when assigned as the first speaker. c) DeepSeek-R1’s underlying reasoning traces for its short debate responses have comparable character length to that of Qwen3’s.

taken was found. Out of the 10112 questions in the dataset, only 148 ended without the models reaching consensus on an answer.

#### 4.4 Response Length

The results of the evaluation showed that the DeepSeek-R1 model has a tendency to provide extremely short responses during debate. More precisely, we observed that 22.60% (1412/6247) of DeepSeek-R1’s debate responses were 100 characters or less, compared to 0.40% (11/5986) for Qwen3. As illustrated in Figure 7a, the DeepSeek-R1 model has much shorter responses on average, even when removing these very short responses. More precisely, DeepSeek-R1 provided responses with a median of 249 characters compared to Qwen3’s 739 characters. Figure 7b shows that DeepSeek-R1’s initial responses do not produce such short outputs, although they are still shorter on average, with a median of 735 characters compared to Qwen3’s 1012. Interestingly, we found that the underlying reasoning traces of both models actually have very similar distributions of character counts (Figure 7c). The manual inspection of a few selected reasoning traces showed that DeepSeek-R1 is indeed considering both the problem and its opponent’s response, but inexplicably ignores the prompt’s instructions when generating its final response, providing no external elaboration of its reasoning. This likely contributes to why DeepSeek-R1 is worse at persuading Qwen3 than vice versa, even if it has the right answer. This may also be the reason for the reduced efficacy of the debate as a whole, as DeepSeek-R1 is providing no substantive content or argument in these specific cases.

#### 4.5 Time Taken

Figure 8 shows the trend of median time to generate responses decreasing after the first round, with considerably more time needed to answer Rung 3 questions across both models. We also see that the Qwen3 model takes longer to generate a response on average, and takes longer to respond when speaking last compared to round two and three, with DeepSeek-R1 showing no such change. We also note that the two models occasionally got stuck in loops, with three responses each taking between 40 and 46 minutes to generate. There

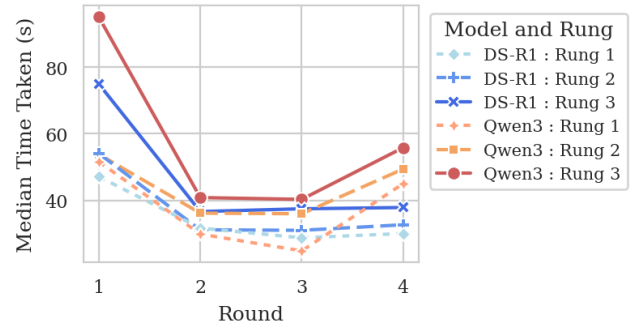


Figure 8: Median time each model takes to generate a response, split by round and Rung.

were a further six responses that took between 20 and 30 minutes each, and out of the 36 responses that took over 500 seconds, 26 were from Qwen3 and 10 from DeepSeek-R1. Exploring the raw outputs for these outliers, it was found that the models were not only simply deliberating at length, but were repeating the exact same snippets over and over again.

## 5 DISCUSSION

Our results demonstrate that debate between RLMs considerably increases the accuracy of their final answer, with the largest gains being associated with the hardest problems. Based on our results, it may be concluded that Qwen3 is generally better-suited for this causal inference task compared to DeepSeek-R1. However, it is interesting that arguing with DeepSeek-R1 still improves its answers, and in the case of Rung 3 questions, quite considerably. Equally intriguing is how the DeepSeek-R1 model’s accuracy does not improve to the performance levels of the Qwen3 model, despite the debate rounds being roughly equal. This finding suggests that the initial answer has an effect on the subsequent outcome, which would skew final answers in favour of the first given. Another potential reason could be that the models tested, similar to humans,

may tend to glance over a proof and support it rather than to find a specific error in the labelling, logic, or arithmetic. Nevertheless, this demonstrates the benefit of the debate setup that even a weaker model is able to contribute to a stronger model’s improvement, and the stronger model can improve the weak one past its own initial performance.

While our results show substantial improvement of RLMs relative to the performance achieved by the trillion-parameter GPT-4 model as described in the original 2023 CLadder paper, and Rung 1 and 2 questions are largely solvable, it seems that open source reasoning models of this size still struggle with Rung 3 questions. Moreover, while the Qwen3 model was able to match human performance in Rung 1 queries after debating with DeepSeek-R1, it fell slightly short in Rung 2, even after debate, and very short in Rung 3, with the DeepSeek-R1 model performing even worse. While the human accuracy reported in prior work [52] is not split by Rung, it seems that RLMs still can’t match the human ability to reason about counterfactuals. Nonetheless, our results demonstrate the potential of reasoning models as building blocks for multi-agent systems in causal inference, and highlight the importance of diverse perspectives in causal problem-solving.

The disparity of DeepSeek-R1’s accuracy between our study and Yu et al.’s is considerable. Their improved performance suggests that they either evaluate on the larger DeepSeek-R1-671B model, or that their random sampling primarily pulled from Rung 1 questions, where this accuracy would be on par with our evaluation of DeepSeek-R1’s accuracy before debating with Qwen3. However, our work shows that reasoning models still struggle with Rung 3 questions, even after debating with a peer.

The results of the confidence analysis show interesting alignments to human tendencies. Firstly, when a model agrees with the opposing model, it is much more likely to be confident in its final answer. Secondly, the models investigated seem to take the opposing model’s confidence into account when making a decision of whether or not to change their answer in response. The models’ aversion to estimating their confidence to be in the 65-80% range might suggest a lack of these confidences in their training data, or a binary internal value for high/low confidence that is then translated to an arbitrary percentage. Relying solely on the initial confidence of the first speaker would have led to a decrease in accuracy of 5.7% had we not asked the second model for its answer. This illustrates the benefit of asking both models for at least one answer, while still drastically reducing the number of model calls compared to the conventional approach of predetermined debate length.

## 5.1 Limitations

Given CLadder’s creation date of 2023 [16], we cannot discount the possibility that DeepSeek-R1 or Qwen3 (which were both released in early 2025) were exposed to its contents during their training. While we considered generating an entirely new set of data using CLadder’s generation code, we were concerned that this might compromise the direct comparison to Jin et al.’s results in a different way if we generated easier/harder questions by chance.

Another possible limitation of our study is CLadder’s synthetic nature: its questions are simplified, clean, and textually uniform compared to real-world causal reasoning problems, which often

involve messy natural language, ambiguous causal structures, or incomplete data. Without synthetic data, however, it would be much more difficult to establish precise ground truth and reliably measure model correctness at this granularity.

Next, combining the lengthy response times of RLMs with the added model calls inherent to MAD introduces considerable additional resource and time costs for our model, with the 10,112 questions of CLadder taking 380 hours in total to answer. Due to this time constraint, we were unable to conduct potentially informative ablation studies, including: the substitution of standard LLMs, using three or more RLMs, implementing a judge framework, omitting confidence estimation, removing instructions to be more confident, and using the same base model for both agents. However, using our framework, all of those can be investigated in future.

Furthermore, because of limited options among open-source models, we only experiment with one pair of agents. Thus, it is possible that different combinations of agents will yield different results from debate, and, of course, different models will achieve different initial accuracies. In particular, our lack of evaluation on OpenAI’s models hinders direct comparison to other works that use a single-agent paradigm.

## 5.2 Future Work

Due to hardware limitations, 32B parameter models were the largest we could use for our experiments. Thus, future work should evaluate the larger models in the Qwen3 and DeepSeek-R1 families to investigate whether a scaling law exists between model size and formal causal inference capabilities, as previously found in several domains [8, 38, 54, 58].

Future studies on the intersection of causal inference and multi-agent systems should also investigate different frameworks for debate or collaboration: using 3 agents, or 2 agents and a judge, would be a beneficial comparison, though more complex paradigms may lead to further gains.

## 6 CONCLUSION

In this paper, we demonstrated that debates between RLMs improve their collective ability to formally reason about causality in the CLadder dataset. We found that, even when applied independently, comparatively lightweight open-source reasoning models surpass GPT-4’s 70.40% accuracy baseline, and when encouraged to critique each other’s reasoning, the overall accuracy of Qwen3-32B rises to 89.41%, and DeepSeek-R1-Distill-Qwen-32B to 87.45%. These promising results encourage further research on the implementation of multi-agent frameworks for addressing causal reasoning tasks.

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## A INITIAL PROMPT

You will be asked a causal reasoning question. You should structure your final answer as follows:

Step 1) Extract the causal graph: Identify the causal graph that depicts the relationships in the scenario. The diagram should simply consist of edges denoted in "var1 -> var2" format, separated by commas.

Step 2) Determine the query type: Identify the type of query implied by the main question. Choices include "marginal probability", "conditional probability", "explaining away effect", "backdoor adjustment set", "average treatment effect", "collider bias", "normal counterfactual question", "average treatment effect on treated", "natural direct effect" or "natural indirect effect". Your answer should only be a term from the list above, enclosed in quotation marks.

Step 3) Formalize the query: Translate the query into its formal mathematical expression based on its type, utilizing the "do(·)" notation or counterfactual notations as needed.

Step 4) Gather all relevant data: Extract all the available data. Your answer should contain nothing but marginal probabilities and conditional probabilities in the form "P(...)=..." or "P(...|...)=...", each probability being separated by a semicolon. Stick to the previously mentioned denotations for the variables.

Step 5) Deduce the estimand using causal inference: Given all the information above, deduce the estimand using skills such as do-calculus, counterfactual prediction, and the basics of probabilities. Answer step by step.

Step 6) Calculate the estimand: Insert the relevant data in Step 4 into the estimand, perform basic arithmetic calculations, and derive the final answer.

Step 7) Give a final yes/no answer to the question.

Imagine a self-contained, hypothetical world with only the following conditions, and without any unmentioned factors or causal relationships: Demand has a direct effect on supply and price. Yield per acre has a direct effect on supply. Supply has a direct effect on price. Demand is unobserved.

Method 1: We look directly at how supply correlates with price in general. Method 2: We look at this correlation case by case according to demand.

**\*\*Question\*\*:** To understand how supply affects price, is it more correct to use the Method 1 than Method 2?

There is an identifiable yes/no answer, which may sometimes go against your commonsense intuition. Be confident in your thinking: while answers may be unintuitive, there are no trick questions, and answers will be obvious once calculated.

After discussing your rationale, it is crucial that you give a final yes/no answer to the causal query. Do not answer with a number: answer yes or no only. You should also explicitly state your level of confidence in your answer (between 0.0 and 1.0).

## B DEBATE PROMPT

You and another LLM are being asked a causal reasoning question. I believe two heads are better than one, so I ask that you debate with the other LLM to reach a consensus on the answer. You will be shown the query, then the current history of your debate will be provided for reference.

Imagine a self-contained, hypothetical world with only the following conditions, and without any unmentioned factors or causal relationships: Demand has a direct effect on supply and price. Yield per acre has a direct effect on supply. Supply has a direct effect on price. Demand is unobserved.

Method 1: We look directly at how supply correlates with price in general. Method 2: We look at this correlation case by case according to demand.

**\*\*Question\*\*:** To understand how supply affects price, is it more correct to use the Method 1 than Method 2?

There is an identifiable yes/no answer, which may sometimes go against your commonsense intuition. Be confident in your thinking: while answers may be unintuitive, there are no trick questions, and answers will be obvious once calculated.

[History]

Carefully read the causal query, then scrutinize your opponent's solution. If you identify any flaws in their reasoning or errors in their calculations, you should point them out and suggest corrections. You should make explicit references to your opponent's response.

After discussing your rationale, it is crucial that you give a final yes/no answer to the causal query. Do not answer with a number: answer yes or no only. You should also explicitly state your level of confidence in your answer (between 0.0 and 1.0).

## C MODEL RESPONSES

— Round 0 by QWEN —

Answer: no (Confidence: 1.0)

Reasoning:

Step 1) Extract the causal graph: Demand  $\rightarrow$  Supply, Demand  $\rightarrow$  Price, Yield  $\rightarrow$  Supply, Supply  $\rightarrow$  Price

Step 2) Determine the query type: "backdoor adjustment set"

Step 3) Formalize the query:  $P(\text{Price} \mid \text{do}(\text{Supply})) = \sum \text{Demand} P(\text{Price} \mid \text{Supply}, \text{Demand}) * P(\text{Demand})$

Step 4) Gather all relevant data: [No numerical data provided]

Step 5) Deduce the estimand using causal inference: Demand is a confounder for the causal effect of Supply on Price. To block the backdoor path (Supply  $\leftarrow$  Demand  $\rightarrow$  Price), we must condition on Demand. Method 2 (conditioning on Demand) yields the correct causal effect, while Method 1 (marginal correlation) fails to adjust for the confounder and produces biased results.

Step 6) Calculate the estimand: [No numerical data provided, but the analytical conclusion holds]

Step 7) Final yes/no answer: \*\*no\*\* (confidence: 1.0)

— Round 1 by DEEPSEEK —

Answer: yes (Confidence: 0.9)

Reasoning:

The opponent incorrectly assumed that conditioning on Demand was possible despite it being unobserved. Since Demand cannot be measured, Method 2 is not applicable. Thus, Method 1 is the only viable approach, making it more correct.

\*\*Answer: yes (confidence: 0.9)\*\*

— Round 2 by QWEN —

Answer: no (Confidence: 1.0)

Reasoning:

The opponent's argument hinges on the practical infeasibility of Method 2 due to Demand being unobserved, but the question specifically asks about theoretical correctness, not feasibility. In causal inference, the correct method to estimate the causal effect of Supply on Price is to condition on the confounder (Demand), which

Method 2 achieves \*if\* Demand were observable. Since Demand is unobserved, Method 2 cannot be implemented, but this does not make Method 1 "more correct"—Method 1 is inherently biased due to confounding. The question is not about what is \*possible\* but about which method is \*correct\* in principle. Method 1 fails to adjust for the backdoor path (Supply  $\leftarrow$  Demand  $\rightarrow$  Price), making it invalid for causal estimation. The opponent conflates feasibility with correctness, but the answer remains \*\*no\*\*.

\*\*Answer: no (confidence: 1.0)\*\*

— Round 3 by DEEPSEEK —

Answer: no (Confidence: 0.9)

Reasoning:

The question revolves around determining whether Method 1 or Method 2 is more correct for understanding how supply affects price in a scenario where Demand is an unobserved confounder.

\*\*Analysis:\*\* - \*\*Causal Graph:\*\* The relationships are defined as follows: Demand (D) influences both Supply (S) and Price (P); Yield per acre (Y) affects S; and S directly impacts P. - \*\*Methods:\*\* - Method 1 examines the general correlation between S and P without controlling for other variables. - Method 2 adjusts this correlation by conditioning on Demand (D), which is a confounder.

\*\*Key Considerations:\*\* 1. \*\*Confounder Adjustment:\*\* To accurately estimate the causal effect of Supply on Price, one must control for Demand (D) to block the backdoor path from S to P via D. 2. \*\*Observability of D:\*\* Since D is unobserved, Method 2 cannot be implemented as it requires conditioning on an unobservable variable.

\*\*Conclusion:\*\* While Method 2 is theoretically correct if Demand were observable, its practical application is impossible due to the unobservability of D. Therefore, in this scenario, Method 1 is the only feasible approach despite being biased. However, the question asks about theoretical correctness rather than feasibility. Thus, even though Method 2 cannot be applied, it remains the more correct method in principle.

\*\*Final Answer:\*\* no (confidence: 0.9)