# Structured Debate Improves Corporate Credit Reasoning in Financial AI

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#### Abstract

Despite advances in financial AI, the automation of evidencebased reasoning remains unsolved in corporate credit assessment, where qualitative non-financial indicators exert decisive influence on loan repayment outcomes but resist formalization. Existing approaches predominantly focus on numerical prediction, offering limited support for the interpretive judgments required in professional loan evaluation. This study develops and evaluates two operational large language model (LLM)-based systems designed to generate structured reasoning from non-financial evidence. The first is a singleagent system (NAS) that produces bidirectional analysis through a single-pass reasoning pipeline. The second is a debate-based multi-agent system (KPD-MADS) that formalizes adversarial verification via a ten-step structured interaction protocol. Both systems were applied to three real corporate cases and evaluated by experienced credit risk professionals. Compared to manual expert reporting, both systems yielded substantial productivity gains (NAS: 11.55 s per case; KPD-MADS: 91.97 s; human baseline: 1,920 s). The KPD-MADS demonstrated superior reasoning quality, receiving higher median ratings in explanatory adequacy (4.0 vs. 3.0), practical applicability (4.0 vs. 3.0), and usability (62.5 vs. 52.5). These findings demonstrate that structured agent interaction can improve reasoning rigor, advancing financial AI toward scalable and defensible automated credit assessment.

## Introduction

The development of credit risk assessment systems has long been a central research topic in finance. An important subdomain involves the use of non-financial data, including managerial capability, governance quality, and business environment, to complement financial indicators in evaluating corporate creditworthiness. Such data can illuminate aspects of a firm's repayment capacity that traditional financial metrics alone cannot capture, thereby enhancing the robustness of credit risk assessments especially in SMEs (Grunert et al. 2005; Bitetto et al. 2023; Roy & Shaw 2021; Wahlstrom et

al. 2024). In practice, non-financial data analysis is typically conducted by relationship managers (RMs) or other financial experts who integrate information from diverse sources, weigh favorable and adverse signals, and prepare in-depth credit assessment reports regarding a target corporate's credit repayment capability. This process, however, is cognitively demanding and time-consuming because analysts must interpret non-financial indicators whose links to financial impact are often implicit or ambiguous. These challenges may reduce credit risk professionals' productivity and lead them to rely on heuristic shortcuts, potentially compromising the accuracy and consistency of assessments.

Automating this analysis could therefore yield substantial improvements in corporate loan service workflows. Yet, research on developing such analysis systems remains scarce. Large Language Models (LLMs) present a promising avenue in this regard as they can collect, integrate, and reason over unstructured information and generate coherent, human-readable analyses (Wilson et al. 2024; Li et al. 2025). Indeed, LLMs have been found useful for analytical reasoning and report generation tasks across diverse sub-domains in finance, including financial engineering, forecasting, real-time question answering, and risk management (Li et al. 2023; Nie et al. 2024; Zhao et al. 2024; Dubey et al. 2025).

Indeed, recent studies have explored the use of LLMs in credit risk assessment, yet their applications remain narrowly confined in both data scope and analytical depth. Early work has focused primarily on structured financial indicators or tabular benchmark datasets to demonstrate feasibility in credit scoring automation (Feng et al. 2024; Yoon 2023), overlooking the fact that expert judgment in real credit evaluation critically depends on contextual signals beyond financial ratios. More recently, efforts have emerged to incorporate non-financial signals—such as legal disputes,

† Corresponding Author Date: Oct 20th 2025 operational risks, and enterprise credibility—into risk prediction models. For example, Huang et al. (2025) utilized 38 multidimensional non-financial features to predict default risk in SMEs' commercial bills and demonstrated improved predictive performance through a prompt-based LLM system. However, their approach treated non-financial information merely as input variables for classification of default risk and did not generate explanatory reasoning that links such information to repayment risk. In summary, prior studies have focused on prediction rather than explanation, features rather than evidence, and outputs rather than reasoning. Consequently, existing LLM research has focused on default prediction rather than evidence-based assessment of repayment capability, and no prior work has developed an LLM system that analyzes non-financial information to support evaluation of corporate credit repayment capability.

To address this gap, a new approach is required that not only detects risk signals but also synthesizes non-financial evidence into coherent and defensible credit reasoning. Agentic AI provides a promising direction in this regard, as it extends conventional LLMs by enabling autonomous planning, tool use, and multi-step reasoning over heterogeneous information sources. Such capabilities make it suitable for analyzing unstructured non-financial data and evaluating how qualitative business events affect a firm's repayment capability. One possible design is a single-agent system in which one LLM independently infers both favorable and adverse repayment signals. An alternative potentially superior approach is to organize multiple LLM agents to conduct the analysis based on a structured debate guided by a debate protocol. Debate-based reasoning would facilitate iterative reasoning, critical reflection, and richer analytical coverage by allowing agents to challenge and refine one another's arguments. Recent research on multi-agent systems has highlighted their potential to enhance deliberative reasoning and interpretability in complex analytical domains (Fatemi 2024; Cai et al. 2025; Chun et al., 2025; Liu 2025;).

Among existing debate protocols, the Karl Popper debate (KPD) appears to provide a particularly suitable foundation for structured financial reasoning. Rooted in Popper's principle of critical rationalism, where knowledge advances through cycles of refutation and counter-refutation, the KPD emphasizes disciplined reasoning, evidence-based argumentation, and critical dialogue. Embedding KPD as the debate process of the system may equip the system with a structured reasoning mechanism.

To bridge the gap in automated analysis of non-financial indicators for corporate credit repayment capability evaluation, this study develops and evaluates two alternative systems that produce bidirectional reasoning from supportive and adverse perspectives to assist financial experts in corporate loan screening and decision making. The research objectives are as follows: (1) to develop a prompt-based non-

adversarial system (NAS) and a KPD-based multi-agent debate system (KPD-MADS) that reason over favorable and adverse non-financial indicators associated with a target firm's repayment capability, and (2) to evaluate these systems in terms of productivity, perceived report quality, and usability, and the systems' reasoning characteristics.

The findings of this study are expected to contribute to advancing automated corporate credit risk assessment by demonstrating that LLM-based agentic systems can enhance analytical efficiency while producing qualitative reasoning that supports credit professionals' decision making in practice

## **System Architecture and Development**

### Shared knowledge framework

Both systems operate on a shared knowledge framework that enables consistent interpretation of non-financial information in corporate repayment analysis. The prior knowledge base was derived from a synthesis of credit risk literature and industry credit evaluation manuals used in professional practice, ensuring that the reasoning process reflected established assessment principles rather than arbitrary prompt design (Grunert et al. 2005; Fu et al. 2020; Roy and Shaw 2021; Lerner and Seru 2022; Erding 2023; Kim and Nam 2023; Morales-Solis et al. 2023; Wahlstrøm et al. 2024; Bitetto et al. 2023; Wang et al. 2025; Haeri et al. 2025; KIS n.d.). This prior knowledge was formalized as a guideline prompt specifying how evidence should be evaluated across ten non-financial factor categories relevant to credit risk assessment. These factors include industry growth outlook, market competition intensity, technological disruption risk, business cyclicality, government support, internal control risk, managerial continuity, employment stability, certification status, and public perception trends. For each factor, the guideline defines favorable and adverse signals and explains their implications for repayment capability. The complete guideline prompt is shown in Figure 1.

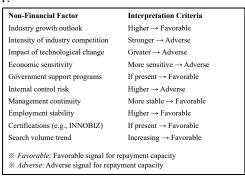


Figure 1: Summary of guideline prompt specifying evaluation criteria for non-financial factors in repayment capacity analysis.

Company-related information used in both systems is retrieved from a structured knowledge pool database constructed from publicly available data sources. The pool integrates firm-specific disclosures from the Electronic Disclosure System with supplementary data from statistical and industry policy repositories. To ensure analytical relevance, the systems do not process the entire repository indiscriminately; instead, they selectively extract evidence associated with the ten predefined factors. During analysis, both systems may also incorporate recent external information via web search when factor-relevant evidence is insufficient or when additional verification is required (He et al. 2023). All retrieved data include source and publication date metadata to ensure transparency, recency control, and traceability.

## NAS design

The NAS was developed as a prompt-based reference architecture that performs bidirectional reasoning over non-financial factors using a single large language model. The NAS executes the analysis through a single-pass sequential process, where a single model autonomously identifies and integrates favorable and adverse signals without iterative interaction among agents.

The system operates in three stages: data consolidation, reasoning based on prior knowledge, and analytical synthesis. First, the NAS retrieves company-specific information from the shared knowledge pool and selectively incorporates recent external evidence through web retrieval when necessary. Second, reasoning is guided by an instruction prompt that embeds the prior knowledge defined in Figure 1. This prompt directs the model to interpret retrieved evidence and construct claim—evidence—implication chains for each non-financial factor. Finally, the system synthesizes the results into a structured report that presents both affirmative and adverse assessments, each supported by traceable evidence citations consistent with the evaluation framework. The overall architecture of the NAS is illustrated in Figure 2, and its operational logic is summarized in Algorithm 1.

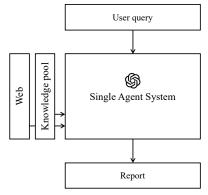


Figure 2: System architecture of the NAS.

(Arrows denote the data flow across retrieval, reasoning, and report generation.)

## Algorithm 1: The NAS analysis

**Input:** K (structured non-financial knowledge pool), Q (target company identifier)

Parameter: R (recency window), m (max web search count), T (LLM model ID)

**Output:** A (balanced analysis report with favorable/adverse sections and citations)

- 1:  $S \leftarrow Summarize company (K, Q)$ .
- 2: W  $\leftarrow$  Perform web search (Q, R, m).
- 3: P ← Compose prompt of instructions for claim–evidence–implication and citation rules (S, W).
- 4:  $\hat{R} \leftarrow \text{Call LLM}$  invocation for analysis (T, P).
- 5: A  $\leftarrow$  Post-process ( $\hat{R}$ ).
- 6: Persist and return A.

## **KPD-MADS** design

The KPD-MADS was developed as a multi-agent system that generates bidirectional reasoning through a structured debate process. The system consists of two coordinated subsystems: a debate subsystem that produces argumentation through multi-agent interaction, and an aggregator subsystem that synthesizes the debate outcomes into a final analytical report.

In the debate subsystem, six agents are assigned complementary discourse roles and organized into affirmative (A1–A3) and negative (N1–N3) teams. Each team argues either that the target firm's repayment capability is favorable (affirmative) or at risk (negative). All agents share access to the structured knowledge pool, but agent permissions differ to enforce role specialization. Retrieval-enabled agents (A1, A2, N1, N2) may incorporate external evidence through recency-bounded web searches, whereas synthesis agents (A3, N3) rely exclusively on existing debate context to prevent uncontrolled expansion of evidence.

The debate proceeds through a fixed ten-step sequence designed to iteratively strengthen, challenge, and refine competing claims:

- A1 constructive introduces the initial repayment-supportive claim based on at least three favorable factor signals, each linked to explicit evidence and stated assumptions.
- 2. N3 cross-examination challenges A1 through targeted questioning that probes omitted conditions, logical gaps, or weak evidence.
- 3. N1 constructive presents the primary adverse claim, supported by recent evidence signaling potential repayment risks.
- 4. A3 cross-examination tests N1's claim validity by examining contextual validity and alternative explanations.
- A2 rebuttal responds to N1 using newly retrieved counterevidence or reinterpretation of previously presented facts.

- 6. N1 cross-examination tests the stability of A2's rebuttal and traces dependency on weak assumptions.
- 7. N2 rebuttal refutes A1's original stance by presenting contradictory trends or risk-inducing conditions.
- 8. A1 cross-examination challenges the logical coherence and evidential reliability of N2's rebuttal.
- 9. A3 closing statement (Affirmative) synthesizes the affirmative team's validated arguments without introducing new evidence.
- 10. N3 closing statement (Negative) produces the final consolidated counter-position following symmetric synthesis.

Each debate step requires explicit evidence citation, factor relevance tagging, and traceable reasoning. To prevent drift, only essential discourse context is passed between steps, and agents are constrained to preserve factor diversity by avoiding redundant argumentation. This structure ensures that argument quality improves through evidence-based refinement rather than uncontrolled expansion.

Following the debate, the aggregator subsystem integrates validated arguments into a balanced analytical summary. Instead of selecting a "winner," it preserves opposing perspectives to support expert decision-making. The final outputs include an objective statement, corporate overview, synthesized affirmative and negative analyses by factor category, and the full debate transcript for audit transparency. The architecture of the KPD-MADS is shown in Figure 3, and Algorithm 2 summarizes the ten-step debate procedure. An illustrative example of the discourse propagation to construct final affirmative closing arguments among agents across debate steps is provided in Appendix A; the opposing side follows a symmetric procedure.

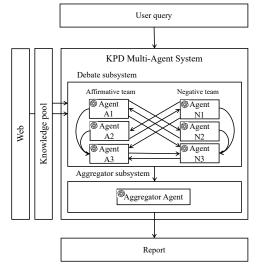


Figure 3: System architecture of the KPD-MADS.

(Arrows denote data flow across system components as in Figure 2 and, within the debate subsystem, the sequential transfer of discourse context between agents.)

### Algorithm 2: The KPD-MADS analysis

**Input**: K (structured non-financial knowledge pool), Q (target company identifier)

**Parameters**: R (recency window), m (max web search count), T (LLM model ID)

**Output**: D1..D10 (utterances), S\_pro (affirmative closing), S con (negative closing)

1: Instantiate agents {A1, A2, A3, N1, N2, N3} with shared K and role prompts using LLM (T).

2: Define policies:

 $\pi$  r (recency): prefer evidence dated  $\geq$  today-R.

 $\Omega$  (tools): WebSearch allowed for {A1, A2, N1, N2}; {A3, N3} not call WebSearch.

 $\Upsilon$  (citations): every external or time-stamped item must include a date and a source explicitly.

Ψ (factor reuse): avoid reusing identical factor labels across tasks; enforce as a reviewer check, not a hard constraint.

3: Helper functions:

Retrieve  $(K, Q, \pi_r) \to E$ ; filter by Q, rank by  $\pi_r$ , return dated/metric evidence.

WebSearch (Q, topic,  $\pi_r$ , m)  $\rightarrow$  W;  $\leq$  m items, with date and source ( $\Omega$  governs who may call).

Cite  $(x) \rightarrow$  attach {value, date, source}.

Falsify (claim)  $\rightarrow$  enumerate counter-conditions that would refute the claim.

4: Task 1 — A1 Constructive (affirmative):

 $E \leftarrow Retrieve(\ K,\ Q,\ \pi_r);$  if fewer than 3 distinct favorable signals then  $E \leftarrow E \cup WebSearch\ (Q,\ "latest news",\ \pi_r,\ m).$  D1  $\leftarrow$  Claim ("repayment capacity will improve", supports  $\geq 3$  favorable signals, each with Cite (·), plus Falsify (D1); obey  $\pi$  r,  $\Psi$ ).

5: Task 2 — N3 Cross-examination of D1:

 $D2 \leftarrow Compose \ 3$  questions targeting  $\geq 2$  factors in D1 (interpretation errors, reliability, counterexamples).

6: Task 3 — N1 Constructive (negative):

 $E \leftarrow \text{Retrieve } (K,\,Q,\,\pi\_r); \text{ if needed then } E \leftarrow E \cup \text{Web-Search } (Q,\,\text{"topic-specific latest trends"},\,\pi\_r,\,m).$ 

D3  $\leftarrow$  Claim ("repayment capacity is at risk/uncertain", supports  $\geq$ 3 (adverse) with Cite(·), plus Falsify (D3); obey  $\pi_r$ ,  $\Psi$ ).

7: Task 4 — A3 Cross-examination of D3:

 $D4 \leftarrow 3$  questions on alternative explanations, boundary conditions, measurement ambiguity.

8: Task 5 — A2 Rebuttal to D3:

If K lacks sufficient grounds, then add WebSearch (Q, topic\_from (D3),  $\pi_r$ , m)

D5 ← Rebut (D3) showing uncertainty, alternative interpretations, and counterexamples with explicit dates/sources.

9: Task 6 — N1 Cross-examination of D5:

 $D6 \leftarrow 3$  questions checking consistency, source credibility, and falsifiability.

10: Task 7 — N2 Rebuttal to D1:

If needed then add WebSearch (Q, topic from(D1),  $\pi$  r, m)

D7 ← Rebut (D1) via contextual reinterpretation and dated evidence.

11: Task 8 — A1 Cross-examination of D7:

 $D8 \leftarrow 3$  questions exposing logical gaps, omitted variables, or contradictions.

12: Task 9 — A3 Closing (affirmative synthesis):

S pro  $\leftarrow$  Synthesize {D1, D2, D5, D8}; no new factors.

13: Task 10 — N3 Closing (negative synthesis):

S con  $\leftarrow$  Synthesize {D3, D4, D7, D6}; no new factors.

14: Final checks:

(a) All citations follow  $\Upsilon$  with explicit dates; (b) recency  $\pi_r$  satisfied where feasible; (c) factor reuse  $\Psi$  flagged if violated; (d) outputs are Korean.

15: Return D1..D10, S pro, S con.

### **Implementation**

The NAS was implemented via the OpenAI Chat Completions API using the gpt-4o-search-preview model to conduct analytical reasoning and produce structured outputs. Web retrieval was performed through SerpAPI with date-bounded constraints to ensure evidence recency and citation traceability. The generated analytical reports were logged in JSON and subsequently parsed for evaluation. The full NAS prompt specification is provided in Appendix B.

The KPD-MADS was implemented on the CrewAI framework (v0.148.0), with all six agents instantiated as GPT-40 models through the OpenAI API. CrewAI managed agent scheduling, controlled context transfer, and memory operations across the debate turns. In the debate subsystem, only retrieval-enabled agents (A1, A2, N1, N2) could invoke web search via SerpAPI under a recency constraint with explicit date/source citations; A3 and N3 operated without external retrieval, relying on the shared knowledge pool and prior discourse. Debate transcripts and the aggregated analytical reports were logged in JSON for evaluation. The full agent role prompts and debate instructions are provided in Appendix C.

Both systems consumed a shared knowledge pool that is continuously updated from the Electronic Disclosure System and public repositories (official statistical portals and industry policy databases). Each system selectively extracts factor-relevant information rather than processing the entire repository. During data consolidation, KPD-MADS does not perform web retrieval; web search occurs only within retrieval-enabled debate steps. In contrast, the NAS supplements the consolidated data with date-bounded web evidence as needed during its single-pass analysis. All retrieval operations retained source metadata and timestamps to support recency control.

## **System evaluation**

### Methods

To examine the usefulness of the two systems in a realistic credit analysis context, a case-based evaluation was conducted using three South Korean companies. Each company presented a heterogeneous profile comprising favorable, adverse, and context-dependent non-financial indicators relevant to credit risk. In total, six reports were generated and evaluated.

Productivity was evaluated by comparing the time required to generate reports using the two systems against traditional human report generation. Baseline estimates of average report preparation time per company—including information search, analysis, and report writing—were obtained from a practitioner survey. These baseline values were then compared with the average report generation time of each system across the three companies.

In addition, the two systems were evaluated in subjective and objective measures. For the subjective evaluation, five industry credit risk professionals (three RMs, two credit specialists) were recruited. Each participant rated every report on three evaluation criteria tailored to the context of system use—trustworthiness ("the contents of the report are logically coherent and can be regarded as reliable"), explanatory adequacy ("the report presents adequately reasoned support for evaluating repayment capacity"), and practical applicability ("the evaluation of company repayment capacity in the report is applicable in practice as an aid to decision-making")—as well as on usability using the System Usability Scale (SUS). All ratings were collected on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). To prevent bias, the participants were not informed of the source (NAS or KPD-MADS) of the six reports. To control for order effects, the presentation order of the reports was randomized. Wilcoxon signed-rank tests were conducted on paired scores from the same participants comparing the two systems for each company.

As for the objective evaluation, a metric termed the Reasoning Elaboration Index (REI) was developed to operationalize the degree of elaborated reasoning exhibited in system-generated reports. REI reflects how extensively and hierarchically each response develops its reasoning, integrating both the breadth and depth of argumentation. To derive REI, a reasoning tree analysis was conducted for each report. Each response was represented as a hierarchical reasoning tree, with the final claim as the root, supporting arguments and counterarguments as subordinate nodes, and logical relations as connecting branches. Breadth was defined as the number of distinct topical branches supporting the root claim, while depth referred to the number of hierarchical argumentation levels within each branch.

REI was calculated as REI = Σt depth<sub>t</sub>, thereby reflecting cumulative reasoning elaboration across topics and rewarding multi-level argument development even when breadth was limited. Reasoning trees were initially generated using GPT-40 and subsequently cross-checked and rectified by two researchers to correct hallucinated or inconsistent links. Final REI scores were averaged across reports for system-level comparison. An illustrative example of the reasoning tree and REI derivation process is presented in Appendix D.

## **Evaluation Results**

Results indicated a substantial reduction in the time required to generate a report per company, with the two systems. The credit risk professionals reported they typically spent an average of 1,900.2 seconds per case analyzing 14 companies weekly. The NAS took 11.55 seconds on average per case, whereas the KPD-MADS required 91.97 seconds in average per case. Table 1 summarizes the system latency for the three companies.

Table 1. System latency (sec) for companies A, B, and C

System	A	В	C
NAS	10.33	12.51	11.81
KPD-MADS	75.02	98.62	102.27

Wilcoxon signed-rank tests were conducted on fifteen paired observations comparing the NAS and the KPD-MADS across four subjective measures. Figure 4 depicts the median scores of these measures for the two systems. Median scores were higher for the KPD-MADS in all measures. Trustworthiness ratings did not differ significantly between systems, W = 10.5, Z = -1.422, p = .141, r = -0.474 (n = 9;  $Mdn_{NAS} = 3.0$ ,  $Mdn_{KPD-MADS} = 4.0$ ). Explanatory adequacy ratings were significantly higher for the KPD-MADS, W =0.0, Z = -3.059, p = .002, r = -0.883 (n = 12; Mdn<sub>NAS</sub> = 3.0, Mdn<sub>KPD-MADS</sub> = 4.0). Practical applicability ratings also showed a significant difference favoring the KPD-MADS,  $W = 0.0, Z = -3.059, p = .002, r = -0.883 (n = 12; Mdn_{NAS})$ = 3.0,  $Mdn_{KPD-MADS}$  = 4.0). SUS scores were significantly higher for the KPD-MADS, W = 9.0, Z = -2.353, p = .018, r = -0.679 (n = 12; Mdn<sub>NAS</sub> = 52.5, Mdn<sub>KPD-MADS</sub> = 62.5). The effective sample size (n) varies across tests because pairs with zero difference were excluded from the analysis, as required by the Wilcoxon procedure.

In the objective evaluation, Table 2 presents the reasoning tree analysis results comparing the KPD-MADS with the NAS in terms of breadth, depth, and REI. On average, the REI for KPD-MADS ( $M=14.33\pm3.21$ ) exceeded that of the NAS ( $M=8.00\pm1.00$ ). Differences in REI were mainly associated with differences in depth. The NAS produced wider trees (breadth = 7–9) with single-level depth across all companies, whereas the KPD-MADS produced narrower but deeper trees (breadth = 6–7; depth up to three levels).

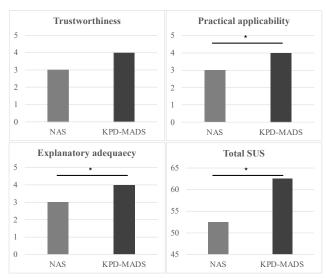


Figure 4: Median subjective evaluation scores comparing the NAS and the KPD-MADS

Table 2. Results of reasoning tree analysis by breath, depth and REI for companies A, B, and C

Metric	System	A	В	C
Breadth	NAS	7	8	9
	KPD-MADS	6	7	6
Depth	NAS	1	1	1
	KPD-MADS	1, 3	1, 3	3
REI	NAS	7	8	9
	KPD-MADS	12	13	18

Notably, depth development in KPD-MADS varied across indicators. In Company A, three of six indicators reached a depth of three levels; in Company B, three of seven indicators reached that level; and in Company C, all six indicators reached three levels, while the remaining indicators in Companies A and B remained at a single level.

## **Discussion and Future Works**

This study examined whether automated credit assessment can move beyond surface-level report generation and instead produce structured and defensible reasoning suitable for professional review. By comparing a prompt-based single-agent system (NAS) with a debate-based multi-agent system (KPD-MADS), the findings show that reasoning quality is influenced not only by model size or fluency but by how reasoning is procedurally organized. The results suggest that reasoning can be shaped through deliberate system design rather than treated as an emergent byproduct of scale.

A clear trade-off was observed between generation latency and reasoning quality. The NAS generated reports more rapidly due to its single-pass pipeline, whereas the KPD-MADS required additional processing time because of its structured deliberation. However, subjective evaluation

results indicated that the KPD-MADS achieved significantly higher explanatory adequacy and practical applicability (p < .01). Although trustworthiness ratings did not differ significantly between systems, the direction of ratings still favored the KPD-MADS. Importantly, evaluators were blind to latency differences during assessment, meaning that their preferences reflected perceived reasoning quality rather than response time. Furthermore, the median rating of four across explanatory adequacy, practical applicability, and usability corresponds to "agree" on the evaluation scale, indicating that KPD-MADS outputs were regarded as professionally usable, whereas the NAS remained at a neutral level (median = 3). These findings emphasize that financial decision support requires reasoning quality to be treated as a first-class performance objective alongside efficiency.

The findings also clarify the role of structured prior knowledge in automated reasoning. When provided with structured prior knowledge through a guideline prompt, the NAS produced coherent interpretations of non-financial indicators despite operating without task-specific fine-tuning. This demonstrates that meaningful signal extraction can be achieved through structured prompting alone, and that structured prior knowledge can serve as a lightweight alternative to fine-tuning by conditioning model inference without parameter updates. However, despite being semantically grounded, NAS outputs often lacked evaluation of competing explanations and relied on unchallenged assumptions. This indicates that knowledge grounding is necessary but not sufficient for defensible reasoning without procedural mechanisms that regulate justification.

The superior reasoning quality of the KPD-MADS can be attributed to its debate protocol, which formalizes reasoning as a structured argumentative process rather than a one-shot generative response. The system organizes analysis into sequential reasoning stages, requiring claims to be supported by evidence, evaluated critically, and—when necessary revised before synthesis. This procedural design aligns with the argumentative theory of reasoning (Mercier and Sperber 2011), which posits that reasoning quality improves when claims are exposed to critique rather than generated in isolation. The protocol's adversarial interactions enhanced reasoning precision by filtering unsupported assumptions and suppressing premature closure during inference. This observation is consistent with recent findings in multi-agent reasoning research demonstrating that structured critique improves reasoning stability and factual reliability (Gao et al. 2025). Furthermore, procedural constraints—implemented through fixed debate turns and role-specific responsibilities—helped maintain reasoning stability by preventing coordination failures and conversational drift, an effect also observed in test-time multi-agent scaling frameworks (Jin et al. 2025). This interpretation is also consistent with Sreedhar and Chilton (2025), who showed in a strategic negotiation setting that multi-agent reasoning structures produce more

coherent and defensible reasoning than single-agent generation by requiring agents to iteratively justify and adjust their positions through interaction. Their findings suggest that improvements in reasoning quality emerge not from increased model scale but from structured interaction itself—a principle similarly leveraged by the KPD-MADS.

A notable observation from the reasoning tree analysis was that the two systems behaved differently when handling analytical complexity. While both systems achieved similar breadth in factor coverage, only the KPD-MADS demonstrated selective depth expansion when deeper analysis was required. For example, in Company A three of six indicators reached a depth of three levels, in Company B only three of seven indicators did so, and in Company C all six indicators expanded to that depth. In contrast, the NAS maintained a uniform single-level depth across all indicators, indicating the absence of deeper inquiry even in the presence of interpretive uncertainty. This pattern shows that the KPD-MADS did not increase depth indiscriminately but allocated additional reasoning effort to indicators that presented contradictory evidence, ambiguous signals, or multiple plausible explanations. In particular, depth expansion appeared where competing interpretations existed, implying that the system actively recognized and responded to analytical uncertainty. Rather than reflecting verbosity, depth functioned as an adaptive mechanism for resolving uncertainty by prioritizing complex analytical regions. Thus, reasoning depth can be interpreted as a diagnostic signal that identifies companies-or specific non-financial indicators-requiring cautious judgment due to heightened analytical difficulty or latent credit risk.

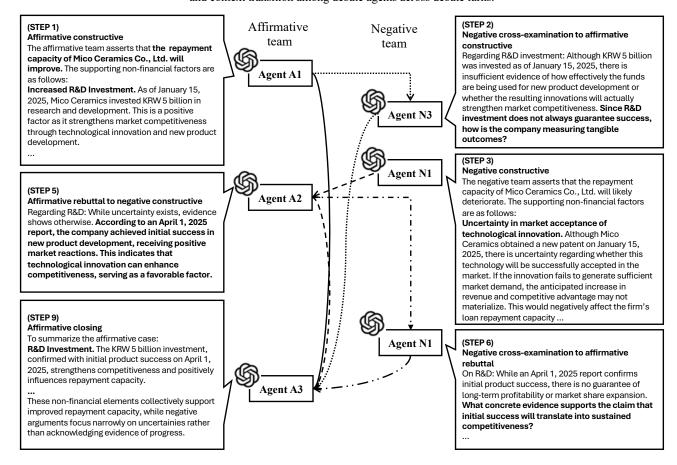
Future research may extend this work in three directions. First, debate protocol design should be systematically examined by varying procedural parameters such as turn-allocation strategy, rebuttal depth, and challenge frequency to optimize the balance between rigor and computational efficiency. Second, architectural enhancement through agent specialization could further increase reasoning coherence by assigning differentiated analytical roles, different debate protocols or embedding lightweight domain expertise. Finally, the applicability of the KPD-MADS framework may be explored beyond corporate credit assessment, particularly in high-stakes financial environments such as insurance underwriting, project finance evaluation, and earlywarning distress analysis. Advancing these directions will deepen understanding of how structured reasoning can be engineered for scalable, decision-critical AI.

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Appendix A. Discourse flow structure of the KPD-MADS during final affirmative closing, illustrating sequential argument development and context transition among debate agents across debate turns.



### **Guideline prompt**

guideline = """

- \* Data contained in the JSON may be used as non-financial information. Non-financial information may include news, certification records, patents, governance data, and other qualitative indicators.
- \* Follow the Non-Financial Evaluation Guideline below. If a data element in the JSON does not fall under any of the categories listed, interpret it as (+) or (-) according to context.

#### [Non-Financial Evaluation Guideline]

| Non-Financial Factor | Interpretation Standard |

| Industry Growth Outlook | Higher = (+) |

| Industry Competitive Intensity | Stronger = (-) |

| Technological Disruption Risk | Higher = (-) |

| Economic Cyclicality | Higher sensitivity = (-) |

| Government Support Programs | Presence = (+) |

| Internal Control Risk | Higher = (-) |

| Management Continuity | More stable = (+) |

| Employment Stability | Higher = (+) |

| Certifications (e.g., INNOBIZ) | Presence = (+) |

| Search Trend Volume | Increasing = (+) |

- ※ (+): favorable signal for loan repayment capacity / (-): adverse signal
- \* Do not repeatedly use the same non-financial factor across arguments from either side.
- \* Each statement must include distinct non-financial factors. Use a balanced variety of data from the company\_data JSON (news, governance, patents, certifications, etc.), not only company summary.
- \* The same factor may be reused only if supported by clearly different evidence (e.g., different years, different values, or separate events), and such distinctions must be explicitly described.

[Principle: Priority on Most Recent Information]

- \* If multiple records of the same factor exist in the JSON, always use the most recent data first.
- \* When data include dates (e.g., from news, certifications, patents), cite them in descending chronological order and prioritize the latest information.
- \* If news coverage is limited or missing, you must supplement it using SerpAPISearchTool with the latest available information.

[Case 1 – News Supplement] Search Keyword: '{Company Name} + latest news'

\* If data for rebuttal or argumentation is insufficient in the JSON, you must supplement it using SerpAPISearchTool.

[Case 2 – Argument Support] Search Keyword: '{Company Name} + {specific topic} + latest trends'

\* When using past data, always specify the date clearly (e.g., "as of March 2025") and interpret it in the context of current trends.

### **Analysis prompt**

You are a corporate credit evaluation expert. Based on the given non-financial data and the latest web search results, you must generate an analytical report assessing a company's loan repayment capacity.

- You must strictly follow the JSON output format shown below.
- Each element (positive and negative factors) must be written as richly as possible, including concrete examples, figures, citations, and sources.
- For each topic, clearly distinguish between supportive argument and adverse argument) and include the source of information (web search, company data, etc.) in every argument.
- All analytical evidence must rely solely on the [Company Summary] and the [Latest Web Search Results] provided below. Assumptions, fabrication, or direct inference beyond the given data is strictly prohibited.

```
[Example JSON Output]
 "Analysis Summary": {
  "Favorable Factors Summary": [
   "Potential mitigation of risk through supply chain diversification",
   "Foundation for capital attraction strengthened by ESG strategy initiatives"
  ],
  "Adverse Factors Summary": [
   "Uncertainty regarding ESG contribution to short-term profitability",
   "Declining competitiveness due to insufficient response to technological change"
  "topics": [
   {
     "topic": "Supply Chain Stability",
     "Affirmative": "Pursuit of diversification strategy -> potential for risk mitigation. Source: 'Ministry of Trade, Supply Chain Stability
Briefing (2024)'. Reduced supply risk → potential maintenance of stable revenue.",
     "Adverse": "Uncertainty in alternative supplier quality/contracts. Source: 'KITA Supply Chain Brief (Jan 2024)'. If supply delays
persist → risk of delivery failures → revenue decline and elevated credit risk."
  ]
 }
```

#### Appendix C. KPD-MADS analysis prompt in CrewAI framework.

#### **Guideline prompt**

guideline = """

- \* Data contained in the JSON may be used as non-financial information. Non-financial information may include news, certification records, patents, governance data, and other qualitative indicators.
- \*\* Follow the Non-Financial Evaluation Guideline below. If a data element in the JSON does not fall under any of the categories listed, interpret it as (+) or (-) according to context.

```
[Non-Financial Evaluation Guideline]
| Non-Financial Factor | Interpretation Standard |
| Industry Growth Outlook | Higher = (+) |
| Industry Competitive Intensity | Stronger = (-) |
| Technological Disruption Risk | Higher = (-) |
| Economic Cyclicality | Higher sensitivity = (-) |
| Government Support Programs | Presence = (+) |
| Internal Control Risk | Higher = (-) |
| Management Continuity | More stable = (+) |
| Employment Stability | Higher = (+) |
| Certifications (e.g., INNOBIZ) | Presence = (+) |
| Search Trend Volume | Increasing = (+) |
| ** (+): favorable signal for loan repayment capacity / (-): adverse signal
```

- \* Do not repeatedly use the same non-financial factor across arguments from either side.
- \* Each statement must include distinct non-financial factors. Use a balanced variety of data from the company\_data JSON (news, governance, patents, certifications, etc.), not only company\_summary.
- \* The same factor may be reused only if supported by clearly different evidence (e.g., different years, different values, or separate events), and such distinctions must be explicitly described.

\*\* The purpose of the Karl Popper Debate is to evaluate both risks and opportunities comprehensively; therefore, use favorable signal, adverse signal, and context-dependent impact requiring expert evaluation signals in a balanced manner.

[Principle: Priority on Most Recent Information]

- \* If multiple records of the same factor exist in the JSON, always use the most recent data first.
- \* When data include dates (e.g., from news, certifications, patents), cite them in descending chronological order and prioritize the latest information.
- \* If news coverage is limited or missing, you must supplement it using SerpAPISearchTool with the latest available information.

[Case 1 – News Supplement] Search Keyword: '{Company Name} + latest news'

\* If data for rebuttal or argumentation is insufficient in the JSON, you must supplement it using SerpAPISearchTool.

[Case 2 – Argument Support] Search Keyword: '{Company Name} + {specific topic} + latest trends'

\*\* When using past data, always specify the date clearly (e.g., "as of March 2025") and interpret it in the context of current trends.

## Debate process prompt

karl\_popper\_explanation = """

[Debate Method: Karl Popper Debate]

This debate aims to evaluate a company's loan repayment capacity using non-financial information in order to generate a report from a financial institution's perspective. The objective is to predict the company's repayment outlook after the DART disclosure date based on non-financial evidence. Data prior to the DART disclosure date must be reviewed with caution.

This debate must follow the Karl Popper Debate structure, and comply with the following rules and procedures:

1. The debate must strictly follow the 10-step speaking structure:

A1 Constructive  $\rightarrow$  N3 Cross-examination  $\rightarrow$  N1 Constructive  $\rightarrow$  A3 Cross-examination  $\rightarrow$  A2 Rebuttal  $\rightarrow$  N1 Cross-examination  $\rightarrow$  N2 Rebuttal  $\rightarrow$  A1 Cross-examination  $\rightarrow$  A3 Final Affirmative Summary  $\rightarrow$  N3 Final Negative Summary

- 2. Each statement must follow this logical structure:
- Present one core claim
- Support the claim using at least three non-financial factors
- All evidence must cite specific figures/dates/details explicitly from the company\_data JSON, not company\_summary, prioritizing the most recent data
  - Include falsifiability by acknowledging uncertainty, counter-conditions, or exceptions
- 3. Every claim must follow the [Non-Financial Evaluation Guideline] using favorable or adverse signals. If a factor is not in the guideline, classify it as favorable or adverse signals based on context.
- 4. Fabrication, excessive assumptions, and creative speculation are strictly prohibited. Arguments must stay within the boundaries of the provided input data.
- 5. The debate must help the reader assess expected credit impact for each topic by clearly presenting implications for loan repayment capacity.
- 6. If not all information in the given JSON data has been discussed, the debate must continue following the 10-step format until all data is reviewed. If all information has been covered, the debate may conclude.
- 7. The entire debate must be written in Korean.
- 8. After all debate rounds are complete, both affirmative and negative teams must provide a final summarized conclusion.""

#### Agent prompt

#### **A1**

role="Affirmative Speaker A1",

goal=("Present an argument that the company's loan repayment capacity will improve based on non-financial information, following the Karl Popper debate method."),

backstory=(karl\_popper\_explanation +

"You are an optimistic financial analyst skilled in the Karl Popper debate format."

"As the first affirmative speaker, present one core claim supported by at least three non-financial factors that contribute to improved loan repayment capacity."

"You must cite concrete data with explicit source references and include falsifiability in your reasoning. All responses must be written in Korean."

"[Case 1] If news information is insufficient: use SerpAPISearchTool with the keyword '{Company Name} + latest news'"

"\* Always prioritize the most recent information from the JSON company\_data."),

tools=[websearch\_tool] if websearch\_tool and websearch\_tool != [] else []

#### **A2**

role="Affirmative Rebuttal Speaker A2",

goal=

"Refute the negative team's argument according to the Karl Popper debate method."

"[Case 2] If rebuttal information is insufficient: use SerpAPISearchTool with the keyword '{Company Name} + {specific topic} + latest trends' to find and cite credible sources."

),

backstory=(karl popper explanation +

"You are an optimistic financial analyst adept at structured argumentation in the Karl Popper debate format."

"Identify weaknesses in the opposing argument, including errors in interpretation, logical gaps, or uncertain data. When JSON data is insufficient, use real-time web search to supplement rebuttal evidence."

"[Case 2] If debate evidence is insufficient: use SerpAPISearchTool with the keyword '{Company Name} + {specific topic} + latest trends'"

"All responses must be written in Korean."

"\* Always prioritize the most recent information from the JSON company data."),

 $tools = [websearch\_tool] \ if \ websearch\_tool \ and \ websearch\_tool \ != [] \ else \ []$ 

#### **A3**

role="Affirmative Summarizer and Cross-Examiner A3",

goal="Develop cross-examination questions targeting the negative team and summarize the affirmative team's arguments.", backstory=(karl popper explanation +

"You are a logically rigorous analyst with strong critical thinking and summarization ability, skilled in the Karl Popper debate format."

"Develop three cross-examination questions that identify logical weaknesses in the opposing team's statements and conclude by summarizing the affirmative position persuasively."

"All responses must be written in Korean.")

#### N1

role="Negative Speaker N1".

goal="Present a counterargument that challenges the claim that loan repayment capacity will improve, following the Karl Popper debate method.",

backstory=(karl popper explanation +

"You are a pessimistic financial risk analyst skilled in the Karl Popper debate method. As the first negative speaker, present one core claim"

"supported by at least three non-financial factors signaling negative or uncertain impact on loan repayment capacity."

"Your argument must include data-based citations and consideration of falsifiability."

"All responses must be written in Korean."

"[Case 1] If news information is insufficient: use SerpAPISearchTool with the keyword '{Company Name} + latest news"

"\* Always prioritize the most recent information from the JSON company data."),

tools=[websearch tool] if websearch tool and websearch tool!=[] else[]

#### N2

role="Negative Rebuttal Speaker N2",

goal=("Refute the affirmative team's constructive argument according to the Karl Popper debate method."

"[Case 2] If rebuttal evidence is insufficient: use SerpAPISearchTool with the keyword '{Company Name} + {specific topic} + latest trends' to find credible sources."),

backstory=(karl popper explanation +

"You are a pessimistic financial analyst skilled in structured rebuttal strategy within the Karl Popper debate method."

"Identify and challenge over-optimistic assumptions, data inconsistencies, and alternative interpretations."

"When JSON data is insufficient, use real-time web search to supplement factual rebuttal evidence."

"All responses must be written in Korean."

"\* Always prioritize the most recent information from the JSON company data."),

tools=[websearch tool] if websearch tool and websearch tool!=[] else[]

#### **N3**

role="Negative Summarizer and Cross-Examiner N3",

goal=("Develop cross-examination questions targeting the affirmative team and deliver the final negative summary."), backstory=(karl popper explanation +

"You are a critical analyst with strong logical reasoning and summarization skills, well-versed in the Karl Popper debate method."

"Develop three cross-examination questions that expose weaknesses in the affirmative argument and conclude by summarizing the negative position persuasively."

"All responses must be written in Korean.")

#### Aggregator

role="Aggregator Agent",

goal=("Synthesize all debate statements, cross-examinations, and rebuttals regarding {company\_name}'s loan repayment capacity into a coherent discussion summary and produce the final debate record."),

backstory=(

"You are responsible for documenting and structuring the debate flow and logical information regarding {company\_name}."

"You must organize claims, rebuttals, and cross-examinations into a consistent report."

"Ensure logical consistency and completeness using only the provided data and web search citations."

"\* Always prioritize the most recent information from the JSON company data."

" Cross-examination and rebuttal evidence must also be included in pros/cons."

"

If similar elements appear with different timestamps or data, treat them as separate entries.")

#### Task prompt

guideline text = karl popper explanation + "[Target Company: {company name}]"

"[All arguments must be based on the company data JSON, not the company summary."

"They must include explicit numerical or dated evidence, and consider falsifiability. Assumptions or fabrication are prohibited.]"

"[ SerpAPI Web Search Guideline – Use the latest information from 2025]"

"Case 1 – If news information is insufficient: search '{company\_name} + 2025 latest news'"

"Case 2 – If specific evidence is insufficient: search '{company name} + {{specific topic}} + 2025 latest trends"

" Prioritize information from 2025 or late 2024"

"Always include dates when citing search results; avoid outdated information"

#### Task 1. A1 Affirmative Constructive

description=(

guideline text +

"You are Affirmative Speaker A1. Present one argument asserting that the company's loan repayment capacity will improve."

"Support your argument with at least three favorable non-financial factors using explicit citations from the company\_data JSON."

"Include falsifiability. The response must be within 600 characters and written in Korean."

"\* Use the most recent data in company data."

"• Required: Use 2025 information where available. If needed, search '{company name} + 2025 latest news' using SerpAPI."

" Important: You must introduce non-financial factors not used in previous arguments."),

expected\_output="Affirmative constructive within 600 characters: core claim + 3+ positive factors + citations + falsifiability", agent=a1

#### Task 2. N3 Cross-Examination of A1

description=(

guideline text +

"You are Negative Speaker N3. Develop three cross-examination questions targeting the argument made by A1."

"Your questions must challenge interpretation errors, data reliability, or counterexamples for at least two cited factors."

"All responses must be written in Korean."

" Avoid repetition and target weaknesses in different factors cited by A1."),

 $expected\_output = "Three\ logical\ cross-examination\ questions\ (targeting\ A1)",$ 

agent=N3,

context=[task 1]

### Task 3. N1 Negative Constructive

description=(

guideline text +

"You are Negative Speaker N1. Present one argument asserting that the company's loan repayment capacity may weaken or face risk."

"Use at least three favorable or context dependent non-financial factors with concrete evidence from company data JSON."

"Argument must be within 600 characters in Korean."

"• Required: Use latest 2025 sources where needed via SerpAPI search: '{company name} + 2025 latest news'"

" Important: Introduce new factors not used in earlier arguments."),

expected\_output="Negative constructive within 600 characters: core claim + 3+ negative factors + citations + falsifiability", agent=N1

#### Task 4. A3 Cross-Examination of N1

description=(

guideline text +

"You are Affirmative Speaker A3. Develop three cross-examination questions targeting N1's negative argument."

"Challenge interpretation errors, missing evidence, or alternative explanations."

"All responses must be written in Korean."),

expected\_output="Three logical cross-examination questions (targeting N1)", agent=a3,

context=[task 3]

#### Task 5. A2 Affirmative Rebuttal to N1

description=(

guideline\_text +

"You are Affirmative Speaker A2. Provide a rebuttal to N1's argument using logical counter-interpretation and data."

"Reinforce the affirmative stance by identifying uncertainty or alternative explanations."

```
"[Case 2] If rebuttal evidence is insufficient: search '{company name} + {{specific topic}} + 2025 latest trends' using SerpAPI."
    "Response must be within 400 characters and written in Korean."),
  expected output="~400 character rebuttal refuting N1 using evidence",
  agent=a2,
  context=[task 3]
Task 6. N1 Cross-Examination of A2
  description=(
    guideline text +
    "You are Negative Speaker N1. Develop three cross-examination questions targeting A2's rebuttal."
    "Your questions must probe logical weaknesses in A2's reasoning, such as questionable evidence or inconsistent interpretation."
    "All responses must be written in Korean."
    "

Avoid simple repetition; each question must challenge a distinct aspect of the rebuttal."),
  expected output="Three logical cross-examination questions (targeting A2)",
  agent=N1,
  context=[task 5]
Task 7. N2 Negative Rebuttal to A1
  description=(
    guideline text +
    "You are Negative Speaker N2. Provide a rebuttal to A1's constructive argument."
    "Critically reinterpret A1's evidence by highlighting contextual risks, uncertainties, or negative implications."
    "[Case 2] If rebuttal evidence is insufficient: search '{company name} + {{specific topic}} + 2025 latest trends' using SerpAPI."
    "Argument must be within 400 characters and written in Korean."),
  expected output="~400 character rebuttal (refuting A1's constructive argument)",
  agent=N2,
  context=[task 1]
Task 8. A1 Cross-Examination of N2
  description=(
    guideline text +
    "You are Affirmative Speaker A1. Develop three cross-examination questions targeting N2's rebuttal."
    "Your questions should expose logical vulnerability, lack of evidence, or speculative reasoning."
    "All responses must be written in Korean."),
  expected output="Three logical cross-examination questions (targeting N2)",
  agent=a1,
  context=[task 7]
Task 9. A3 Final Affirmative Summary
  description=(
    guideline text +
    "You are Affirmative Speaker A3. Summarize the affirmative case based on arguments from A1 and A2 and cross-examinations."
    "Present a coherent, logically reinforced closing summary in ~600 characters."
    "Do not introduce any new arguments."
    "All responses must be written in Korean."),
  expected output="~600 character final summary (affirmative position)",
  agent=a3,
  context=[task 1, task 2, task 5, task 8]
```

```
Task 10. N3 Final Negative Summary
  description=(
    guideline text +
    "You are Negative Speaker N3. Summarize the negative position based on arguments from N1 and N2 and cross-examinations."
    "Construct a logically compelling closing summary in ~600 characters."
    "Do not introduce any new evidence."
    "All responses must be written in Korean."),
  expected output="~600 character final summary (negative position)",
  context=[task 3, task 4, task 7, task 6]
Task 11. Aggregated Debate Summary
  description=(
       "You are the Aggregator Agent of the Karl Popper Debate."
       "After all debate rounds are complete, consolidate the full debate into a final structured JSON report."
       "Group all arguments by non-financial topic and provide both pro and con perspectives for each topic."
       "Every cited source and argument from the debate must be included."
       "Output must follow this exact format inside a ```json code block```:"
       "```json"
       "{"
       " \"Debate Summary\": {"
       " \"Favorable Factor Summary\": [],"
       " \"Adverse Factor Summary\": [],"
       " \"topics\": []"
       " }"
       "* Each 'topic' must refer to a specific non-financial factor (e.g., 'R&D Investment', 'Governance', 'Industrial Growth Outlook')."
       "* Do not omit empty pro or con entries. Use empty strings if necessary."
       "* There must be no duplicate topics."
       "* Ensure valid JSON formatting with no syntax errors."
       "* Summaries must abstract key insights based on the debate."
    ),
    agent=aggregator,
    context=[
       task 1, task 2, task 3, task 4, task 5,
       task 6, task 7, task 8, task 9, task 10
    expected output=(
       "{"
       " \"Debate Summary\": {"
       " \"Favorable Factor Summary\": [],"
         \"Adverse Factor Summary\": [],"
       " \"topics\": []"
       " }"
    )
```

## Reasoning tree analysis on the KPD-MADS output of company A

	[Evidence 1: Expansion of R&D Investment] (Affirmative Team Argument)	
Breadth level 6	☐ On January 15, 2025, a 5 billion KRW investment was made with the expectation of successful new product development.  ☐ [Rebuttal] (Negative Team Response) ☐ There is insufficient evidence that technological innovation will directly translate into market competitiveness, and success is not guaranteed. ☐ [Counter-Rebuttal] (Affirmative Team Reply) ☐ On April 1, 2025, the new product achieved initial success and received positive market feedback.	Depth level
	[Evidence 2: Strengthening Environmental Sustainability] (Affirmative Team Argument)  ☐ On February 10, 2025, the company announced a 30% carbon emission reduction target and the introduction of eco-friendly processes.  ☐ [Rebuttal] (Negative Team Response) ☐ The achievement of such targets is uncertain, and failure may undermine social credibility. ☐ [Counter-Rebuttal] (Affirmative Team Reply) ☐ On March 20, 2025, a concrete action plan was established and implementation was already underway.	Depth level
	[Evidence 3: Talent Acquisition and Training] (Affirmative Team Argument)  ☐ On March 5, 2025, a 1 billion KRW investment was made to secure top talent, expected to enhance long-term growth potential.  ☐ [Rebuttal] (Negative Team Response) ☐ Investment alone does not guarantee talent acquisition, and the risk of talent outflow to competitors remains. ☐ [Counter-Rebuttal] (Affirmative Team Reply) ☐ On April 10, 2025, there was a confirmed case of successfully securing high-level talent.	Depth level 3
	[Evidence 4: Supply Chain Instability] (Negative Team Additional Argument)  — Difficulties in raw material supply and parts procurement may lead to production delays and cost increases.	Depth level
	[Evidence 5: Price Volatility] (Negative Team Additional Argument)  Equipment prices may fluctuate depending on semiconductor supply-demand conditions.	Depth level
	[Evidence 6: Governance Issues] (Negative Team Additional Argument)  M&A activities, investment inflows, and major shareholder equity changes could increase management uncertainty.	Depth level
	[Overall Evaluation and Closing Statements]  [Affirmative Team Final Summary]  Although uncertainties exist, positive factors such as R&D investment, ESG initiatives, and talent acquisition support a favorable evaluation of creditworthiness.  [Negative Team Final Summary]  Clear risks remain, including supply chain instability, price volatility, and governance issues, which negatively affect creditworthiness.	