PartnerMAS: An LLM Hierarchical Multi-Agent Framework for Business Partner Selection on High-Dimensional Features

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Abstract

High-dimensional decision-making tasks, such as business partner selection, involve evaluating large candidate pools with heterogeneous numerical, categorical, and textual features. We propose PARTNERMAS, a hierarchical multi-agent framework that decomposes evaluation into three layers: a Planner Agent that designs strategies, Specialized Agents that perform role-specific assessments, and a Supervisor Agent that integrates their outputs. To support systematic evaluation, we also introduce a curated benchmark dataset of venture capital co-investments, featuring diverse firm attributes. Across 140 cases, PARTNERMAS consistently outperforms single-agent and debate-based multi-agent baselines, achieving up to 10–15% higher match rates. Reasoning analysis shows that planners are most responsive to domain-informed prompts, specialists produce complementary feature coverage, and supervisors play an important role in aggregation. Our findings highlight that structured collaboration among agents can produce more robust outcomes than scaling individual models, highlighting PARTNERMAS as a promising framework for high-dimensional decision-making in data-rich domains. Our code is available here.

1 Introduction

In real-world decision-making, practitioners often navigate high-dimensional data including extensive option sets and numerous evaluative features (Sandanayake et al., 2018; Sigle et al., 2023). Business partner selection which includes partner shortlisting and strategic alliance formation exemplifies this challenge (Mindruta et al., 2016): firms often face a vast pool of potential candidates, each described by diverse attributes ranging from quantitative indicators (*e.g.*, financial metrics, geographic presence) to text-rich information (*e.g.*, strategic fit, investment preferences) (Shah and Swaminathan, 2008). The scale and complexity of such data can easily overwhelm human decision-makers, incurring significant costs (Li et al., 2008). This underscores the need for intelligent systems capable of analyzing large candidate sets and diverse features.

Large language models (LLMs) have emerged as promising tools for addressing reasoning tasks in data-rich domains (Lee et al., 2025; Mischler et al., 2024). With appropriate prompting or information retrieval techniques, these models can identify salient features using only feature and task descriptions, achieving performance comparable to established methods (Li et al., 2025a; Jeong et al., 2024). As task complexity has increased, researchers have moved beyond single-agent approaches toward multi-agent systems (MAS), wherein complex problems are decomposed into specialized sub-tasks managed by agents within defined workflows (Li et al., 2024b). Recent studies have demonstrated the potential of MAS in diverse domains, including software development (Tao et al., 2024), mathematical reasoning (Li et al., 2025b), and healthcare decision-making (Chen et al., 2025).

Despite these advances, a significant gap remains in applying MAS to high-dimensional tasks within high-stakes domains such as finance, where effective automation could reduce expert burden while improving decision quality. Current research on financial MAS has focused on a few applications, such as individual stock trading (Yu et al., 2024) and portfolio management (Luo et al., 2025), leaving critical financial decision-making areas underexplored. This study addresses business partner selection as a representative example, where MAS must handle high-dimensional, heterogeneous features. This setting requires both scalability and nuanced feature reasoning that previous MAS works have not sufficiently explored.

To address this gap, we develop PARTNERMAS, a hierarchical MAS framework for shortlist generation over high-dimensional, mixed-type tabular features. Unlike generic role-based MAS or

debate-style systems, PARTNERMAS couples dynamic role generation conditioned on task context, role-specific feature selection over heterogeneous candidate attributes, and supervisor-level aggregation that separates consensus from conflict resolution. This design supports reasoning over large candidate pools without task-specific training while preserving interpretable intermediate decisions. To summarize, this research makes two key contributions: (i) We introduce a tabular benchmark for historical co-investor shortlisting, providing a realistic testbed for evaluating LLM reasoning over mixed numerical, categorical, and textual business features. (ii) We design and evaluate PARTNERMAS, showing that structured planner–specialist–supervisor coordination improves shortlist recall over single-agent and debate-based MAS baselines and yields reusable design insights about role diversity, feature focus, and aggregation.

2 Related work

High-dimensional data refers to datasets characterized by large heterogeneous features (Tang et al., 2016). These settings pose well-documented challenges (Johnstone and Titterington, 2009) for traditional machine learning (ML) and LLM-based methods, including overfitting (Kim and Simon, 2014), feature redundancy (Ferreira and Figueiredo, 2012), and difficulties in interpreting model outputs (Potts and Schmischke, 2021). Our work focuses on business partner selection, which inherently involves high-dimensional information.

Business Partner Selection. Selecting partners is a crucial first step in establishing business relationships (Shah and Swaminathan, 2008). Prior research highlights central drivers of partner selection, including value creation and trustworthiness. Firms often evaluate potential partners based on complementary resources and capabilities like knowledge, technology, or capital, to assess whether collaboration generates greater value than independent efforts (Furlotti and Soda, 2018; Mindruta et al., 2016). Meanwhile, trustworthiness is essential to mitigate risks from opportunistic behavior (Das and Rahman, 2010; Li et al., 2008), often inferred from past collaborations or transaction records (Lumineau et al., 2021). Beyond value and trust, firms weigh coordination costs, which can arise from communication needs, geographic distance, or cultural differences (Gulati et al., 2012).

In the venture capital (VC) sector (our focus), co-investor selection often begins with a broad search for potential partners. After compiling an initial list, experienced managers evaluate multiple factors to identify firms that align with their objectives. The lead VC then invites shortlisted candidates, initiating bilateral negotiations. However, this process is often lengthy and labor-intensive, recognized as a major ex-ante transaction cost in business exchanges (Lumineau et al., 2021). This presents the need for more intelligent and efficient methods.

LLM-driven Feature Selection. By leveraging pretrained knowledge, LLMs can rank, filter, or explain the importance of features (Jeong et al., 2024). Jeong et al. (2024) developed pipelines where LLMs generate feature importance scores or explanations. Li et al. (2025a) showed that LLMs can reliably identify key predictors in domains like healthcare and finance. In biomedical settings, researchers have retrieved definitions of gene or protein identifiers to ground LLM reasoning (Lee et al., 2025). Such LLM-driven selectors can rival statistical feature selection techniques (*e.g.* LASSO) even in zero-shot settings (Zhang et al., 2025).

Beyond single LLM, researchers have increasingly turned to MAS for complex decision-making. In MAS, agents assume specialized roles, such as planner, critic, or domain expert, and interact through structured workflows. For instance, MetaGPT assigns LLM agents to emulate software development teams (Hong et al., 2024), while debate-style frameworks allocate agents to critique and refine reasoning in math and coding tasks (Chan et al., 2024; Liang et al., 2024). Similar approaches in healthcare show that a "generalist" can triage cases and delegate to specialists for targeted diagnosis (Zuo et al., 2025). Some recent work applies MAS to feature engineering, where selector, generator, and coordinator agents refine feature sets (Gong et al., 2025). Additional review of MAS and tabular LLMs is presented in Appendix C. However, applying MAS to high-dimensional business data remains underexplored, and little evidence shows how role-specialized agents can coordinate to produce feature-informed decisions. This gap motivates our exploration of LLM-based MAS for business partner selection.

3 Methodology

3.1 Problem Formulation

Figure 1 illustrates our MAS architecture design. We specifically examine how the lead VC evaluates the initial candidate pool to create a more targeted shortlist (Figure 1 (A)). We consider the

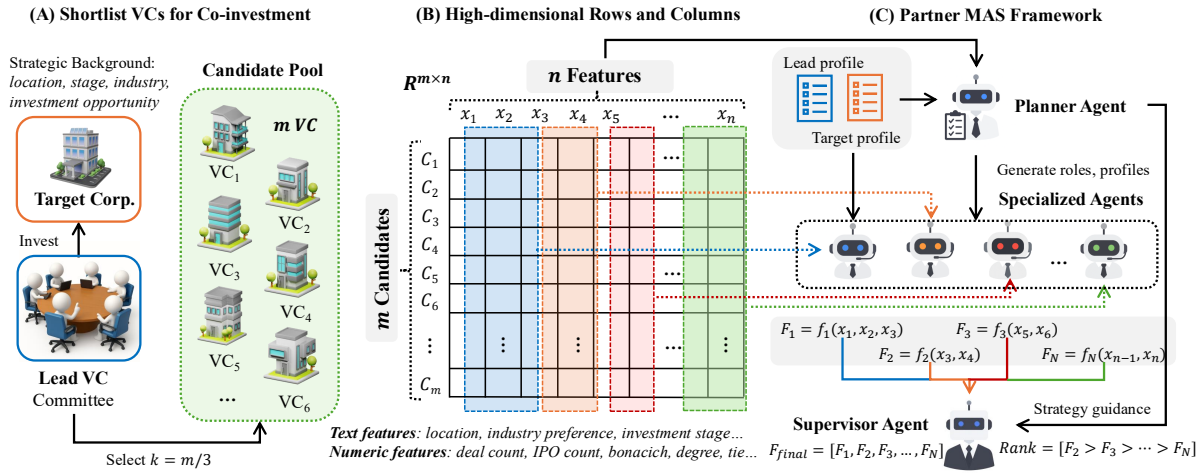

Figure 1: An illustration of the research design. (A) Co-investors shortlisting. (B) High-dimensional feature selection. (C) Hierarchical MAS framework.

candidate pool as high-dimensional, heterogeneous tabular data with m candidates (rows) and n features (columns) (Figure 1 (B)). Let it be $C = \{c_1, \ldots, c_m\}$, where each candidate c_j is represented by a feature vector $x_j \in R^n$, and the feature matrix is $X \in R^{m \times n}$. Columns are mixed-type, consisting of both text fields (*e.g.*, investment preference, firm type, industry preference) and numeric attributes (*e.g.*, deal count, IPO count, network degree, tie strength). Given a task context $\mathcal{Q}$ (*e.g.*, lead VC and target company profiles), the goal is to produce a shortlist $S = (s_1, \ldots, s_k)$, where $S \in C^k$ and $k = \lfloor m/3 \rfloor$, *i.e.*, the top $\lfloor m/3 \rfloor$ candidates from the pool. The proportion is set to one-third to emulate a realistic VC screening process, where a large pool of candidates is progressively narrowed down. For instance, an initial pool of 36 candidates is filtered to a shortlist of 12, from which a final group of four co-investors is selected (feature description detailed in Appendix D).

3.2 MAS Architecture Design

To tackle the challenge of partner selection, we introduce a hierarchical MAS framework called **PartnerMAS** (Figure 1 (C)). This design enables the system to decompose the high-dimensional task into manageable sub-tasks, each assessing tabular data from different dimensions: (i) **Planner Agent** (PA) that designs the evaluation strategy. (ii) **Specialized Agents** (SA), $\{SA_1, \ldots, SA_N\}$, which are dynamically configured by PA to execute this strategy based on their role and expertise. (iii) **Supervisor Agent** (SPA) that aggregates analyses to make a decision.

Planner Agent (PA). The primary role of PA is to interpret the high-level task context $\mathcal{Q}$ (Lead VC and target company profiles) and formulate an evaluation plan. It does so by analyzing $\mathcal{Q}$ with feature names to identify the most critical evaluation dimensions given the case description. The PA's output is a set of N agent configurations, $\{A_1, \ldots, A_N\}$, where each configuration A_i contains a specific "profile" that guides the corresponding SA_i. It also generates "strategic guidance" to support the decision for the SPA. Formally, the output can be expressed as: $[\{A_1, \ldots, A_k\}, PA(\mathcal{Q}, C_{sample})]$, a set of explicit instructions for the team of SAs.

Specialized Agent (SA). Each SA acts as a domain expert, tasked with evaluating the entire candidate pool C from its specialized perspective. To manage the high dimensionality of the candidate feature vectors ($x_j \in R^n$), the SA first performs a feature selection step. Guided by its assigned $profile_i$, it identifies and focuses on a relevant feature subset. The agent's core evaluation function f_i, driven by a backbone LLM, then directly produces a ranked shortlist of candidates. This output, S'_i, is a list containing the top $k' = \lceil m/3 \rceil$ firms, where each entry includes the firm's ID, its rank, and an alignment score, $score_{ij} \in [1, 10]$.

Supervisor Agent (SPA). The SPA is responsible for synthesizing the shortlists $\{F'_1, \ldots, F'_N\}$ from Specialized Agents into the final ranked list F. It mimics a human-led committee's decision-making process by first establishing consensus and then resolving disagreements based on the strategic priorities of the deal. This is achieved in a two-step process: (i) **Consensus Selection**: The SPA first identifies candidates with broad support across SA, by counting how many agents include them in their shortlists. This step can determine

robust candidates that perform well across different dimensions: $F_1(c_j) = \sum_{i=1}^{N} I(c_j \in F_i')$. (ii) **Conflict Resolution**: To fill the remaining slots in the shortlist, the SPA resolves disagreements among the SAs. It first determines an importance weight w_i for each agent based on the agent's relevance to the specific deal. It then resolves the conflict for the remaining candidates by giving more weight to the opinions of more important SAs. This allows the SPA to select candidates who excel in critical areas, even if they lack broad consensus: $F_2(c_j) = \sum_{i=1}^{N} w_i \cdot \frac{1}{R_i(c_j)}$. The final shortlist $F = [F_1(c_j), F_2(c_j)]$.

3.3 Evaluation

The system's performance is evaluated against observed historical co-investor selections. We do not treat these records as globally optimal partner choices; rather, they provide behavioral labels for whether a method can recover the partners that lead VCs actually shortlisted or selected under the observable information available in our dataset. For each task, the generated shortlist F is compared to the set of observed co-investors, G. The primary metric is the **Match Rate**, which measures the fraction of historical partners that are recovered by the generated shortlist. It is formally defined as the recall of the system:

$$\text{Match Rate} = |F \cap G|/|G| \times 100\%. \quad (1)$$

For instance, if the initial candidate pool has 36 VC firms ($m = 36$), our PARTNERMAS generates a shortlist of 12 ($k = 12$). If the observed co-investor set contains 4 firms ($|G| = 4$) and 3 are found within the system's shortlist ($|F \cap G| = 3$), the Match Rate is 75%. This metric evaluates historical shortlisting alignment rather than ex-post investment quality. Additional evaluation metrics (e.g., ranking-based) are presented in Appendix I.

4 Experiment Design

4.1 Data Preparation

Our primary data source is the London Stock Exchange Group (LSEG) Workspace (London Stock Exchange Group, 2024), from which we collect VC investment records from 1980 to 2024. Following prior VC research (Makarevich, 2018; Wang et al., 2022), we restrict the sample to U.S.-based companies to avoid confounding effects from cross-country regulatory and institutional differences. We further exclude solo investments to focus on co-investments, where collaboration among investors is observable. After this initial filtering, the dataset comprises 52,662 companies backed by 16,030 VC firms, and we identify all active VCs in each year, industry, and state to construct the relevant candidate pool for each year–state–industry context.

To examine multiparty syndicate formation, specifically how lead VCs select co-investment partners, we further restrict the sample to companies with complete first-round information and syndicates of at least three investors. We then merge the company list from LSEG with PitchBook (PitchBook Data, Inc., 2024) to identify the lead VC for first-round investment based on company name and headquarter state. Only matches labeled as "high" or "very high" confidence are retained to ensure accurate lead investor identification. For analytical tractability, we limit the sample to cases with a single lead VC, since multiple leads often involve more complex governance and negotiation dynamics (Lerner, 2022; Kaplan and Strömberg, 2003). After these filters, the sample includes 2,218 companies. We then merge PitchBook data back into the LSEG sample to retrieve lead VC information, supplemented by manual matching (company name, VC firm name, industry, and state) and excluding samples without necessary information. Applying all restrictions yields a final dataset of 140 cases for subsequent analysis [1].

To reduce name-based memorization, all company and VC firm names are removed from prompts. Candidate firms are shown to agents only through anonymized IDs and structured attributes. Thus, the task requires feature-based ranking within a year–state–industry candidate pool rather than direct retrieval of known company–investor relationships.

4.2 Experiment Settings

We evaluate multiple experiments for partner selection. All experiments use the same dataset and evaluation protocol, and all LLMs are run with temperature 0 to minimize output variance.

Baseline Configurations: Single Agent. In this baseline, a single LLM agent reviews all candidate firms and produces a ranked shortlist without external feedback. The parameter k denotes the number of independent runs: k=1 corresponds to a one-shot evaluation, while $k > 1$ allows the agent to generate multiple candidate shortlists. To obtain a final decision, the agent engages in self-reflection,

[1] Due to intellectual property constraints of VC firms, the dataset cannot be released publicly but is available from the authors upon request for pure research purposes.

comparing its own k outputs and selecting the one it deems most reliable. This design tests both the limitations of single-pass reasoning and the benefits of repeated deliberation within a single-agent framework. Unless otherwise specified, we set k=1 by default. The details for the Single Agent prompts are shown in Appendix N.2.

Baseline Configurations: Debate MAS. The second baseline implements a debate-based multi-agent system (MAS) inspired by prior work (Chan et al., 2024; Liang et al., 2024). Three specialized agents simulate a VC committee: each independently evaluates candidates, critiques peers' reasoning while scores remain hidden, and then revises its judgments. A supervisor agent synthesizes their inputs into a final shortlist. The details for the Debate MAS design and prompts are shown in Appendix H and Appendix N.3.

Agent Configuration: PARTNERMAS. Our MAS adopts the Planner–Specialist–Supervisor design described in Section 3. Unlike Debate MAS, which emphasizes adversarial critique, PARTNERMAS is built on structured collaboration and coordinated division of labor. Its design varies along two dimensions: prompt guidance and backbone assignment. For prompts guiding the Planner Agent and Supervisor Agent, we compare two conditions: (i) generic prompts without business knowledge, and (ii) business-domain guided prompts, which encourage agents to consider collaboration networks, industry fit, financial capacity, and geography (details in Appendix N). The details for the PARTNERMAS prompts are shown in Appendix N.4.

5 Experimental Results

5.1 Performance Benchmarking

We first compare the overall performance of PARTNERMAS against Single Agent and debate-based MAS baselines by match rate across all business cases. To contextualize the results against structured matching methods, Appendix J further compares PARTNERMAS with supervised and unsupervised ML baselines, including similarity-based retrieval and clustering-based selection. Results are summarized in Figure 2. These additional baselines show that PARTNERMAS remains competitive without task-specific training and provides stronger top-rank recommendation quality.

PARTNERMAS achieves the strongest results. Our hierarchical multi-agent system consistently outperforms all baselines. For example, PARTNERMAS with gpt-4.1-mini as the backbone achieves

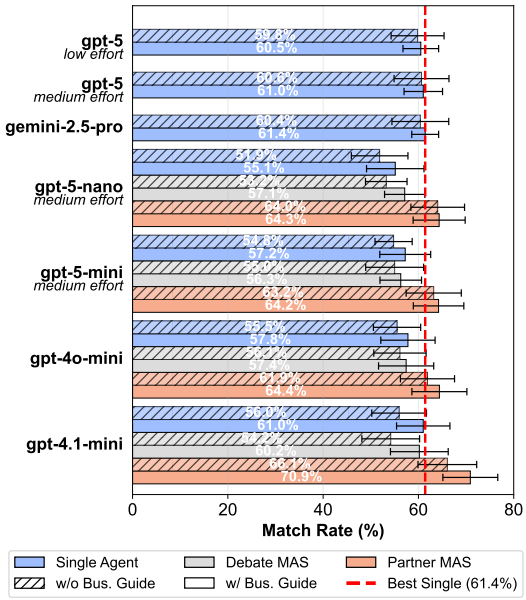

Figure 2: Performance benchmark for Single Agent, Debate MAS, and PARTNERMAS.

a match rate of 70.89% with business-domain guided prompt, exceeding the best-performing single LLMs, such as gpt-5 (medium effort) (61.50%) and gemini-2.5-pro (61.42%). Notably, gpt-4.1-mini is smaller and more cost-efficient, with token cost roughly an order of magnitude lower than gpt-5 or gemini-2.5-pro, yet delivers markedly stronger outcomes when embedded in PARTNERMAS. This pattern holds even with smaller backbones like gpt-5-nano, where PARTNERMAS still delivers 8–10% higher match rates than the same model in a Single Agent configuration. These results underscore that coordination among specialized agents can compensate for and often surpass pure model scaling, and the gains remain robust across different LLMs.

Debate alone does not guarantee improvements. We next assess whether adversarial interaction between agents helps. The debate-based MAS baseline sometimes produces modest gains over Single Agent baselines (*e.g.*, 57.12% for gpt-5-nano in Debate MAS vs. 55.14% for its Single Agent counterpart). However, the overall effect is inconsistent: for gpt-4.1-mini, Debate MAS reaches only 60.19%, lagging substantially behind PARTNERMAS with the same backbone, and in some cases performance drops below the Single Agent level. A likely explanation is that debate can distract agents from their original reasoning or amplify minor errors, rather than guide them toward stronger solutions. This finding shows that while debate can reveal reasoning errors, it lacks the structured role division and aggregation mecha-

Table 1: Match rates (mean ± 95% CI) across different settings. All gpt-5-nano adopt the medium thinking.

PA	SA	SPA	Match Rate
gpt-4o-mini	gpt-4o-mini	gpt-4o-mini	64.4% ± 5.8
gpt-4.1-mini	gpt-4o-mini	gpt-4o-mini	63.2% ± 5.8
gpt-5-nano	gpt-4o-mini	gpt-4o-mini	65.2% ± 5.9
gpt-4o-mini	gpt-4.1-mini	gpt-4o-mini	62.1% ± 6.0
gpt-4o-mini	gpt-5-nano	gpt-4o-mini	64.7% ± 5.5
gpt-4o-mini	gpt-4o-mini	gpt-4.1-mini	69.0% ± 5.9
gpt-4o-mini	gpt-4o-mini	gpt-5-nano	64.7% ± 5.5

nisms needed for complex business tasks.

Business-domain guidance helps. To verify the effect of business domain knowledge, we compare model performance with and without business-domain guidance. The guidance text is shown in Appendix N.1. Across nearly all models, domain guidance yields consistent, though marginal, accuracy gains. For Single Agent baselines, it improves match rates by 2–5% absolute, such as for gpt-4.1-mini (55.95%). The improvements are larger for PARTNERMAS, with some configurations gaining over 7%, rising from 62.55% to 69.03%. These results show that grounding agents in domain-relevant dimensions—such as financial capacity, collaboration networks, or geographic compatibility—enhances shortlist quality. The magnitude varies across models, indicating that stronger backbones better exploit domain cues, while smaller models benefit but plateau earlier.

Backbone LLM effects. In Table 1, among Single Agent baselines, gpt-4.1-mini achieves the highest match rates when business domain guidance is provided, followed by gpt-4o-mini, while gpt-5-nano (medium effort) generally lags behind. This suggests medium-sized models balance reasoning ability and efficiency, whereas smaller models underperform and larger ones may not justify their cost. When incorporated into PARTNERMAS, however, even lightweight models like gpt-5-nano (medium effort) gain from structured role division, achieving 8–10% higher match rates relative to their Single Agent counterparts. These findings highlight that the hierarchical design not only amplifies the capabilities of stronger backbones but also compensates for the weaknesses of smaller ones, yielding robust improvements.

Performance–efficiency tradeoff. Figure 3 illustrates the trade-off between match rate and token consumption. To ensure fairness, we evaluate Single Agent baselines with k=4 runs, aligning their computational cost with Debate MAS (3+1 agents)

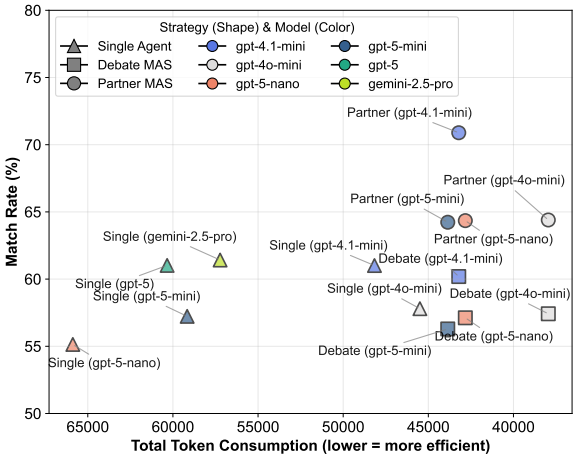

Figure 3: Model performance comparison.

and PARTNERMAS (average of 4.27 agents). The results show that large single models such as gpt-5 and gemini-2.5-pro fall into a high-cost but moderate-accuracy regime. In contrast, PARTNERMAS configurations consistently deliver higher match rates with lower token budgets. For example, PARTNERMAS with gpt-4.1-mini achieves over 70% accuracy while consuming fewer tokens than gpt-5 (medium effort). This efficiency arises from decomposition: specialized agents narrow their focus to smaller feature subsets, reducing redundancy and improving coordination. Consequently, PARTNERMAS proves more accurate and cost-effective, making it well suited for practical deployment where API costs and inference latency are critical constraints.

5.2 Performance and Reasoning Analysis

To understand the internal dynamics, we analyze agent performance (Figure 4) and use regression models to examine reasoning across the PARTNERMAS hierarchy. We evaluate the Planner Agent's deployment strategy with logistic and linear regression (Table 2), visualize Specialized Agents' performance and feature focus with heatmaps (Figure 5), and assess the Supervisor Agent's decision-making through regression analysis (Table 7). Additional Supervisor aggregation analyses are presented in Appendix K and Appendix L. The analysis shows how backbones and business-domain guidance shape agent reasoning and performance.

System and agent performance. Figure 4 shows the performance of Specialized Agent clusters (see Appendix G for details on handling variations in Specialized Agent names), which achieve 65% to 75% accuracy with less than $45k$ token usage. Sub-figure (A) relates cluster performance to usage and importance. Partnership History and

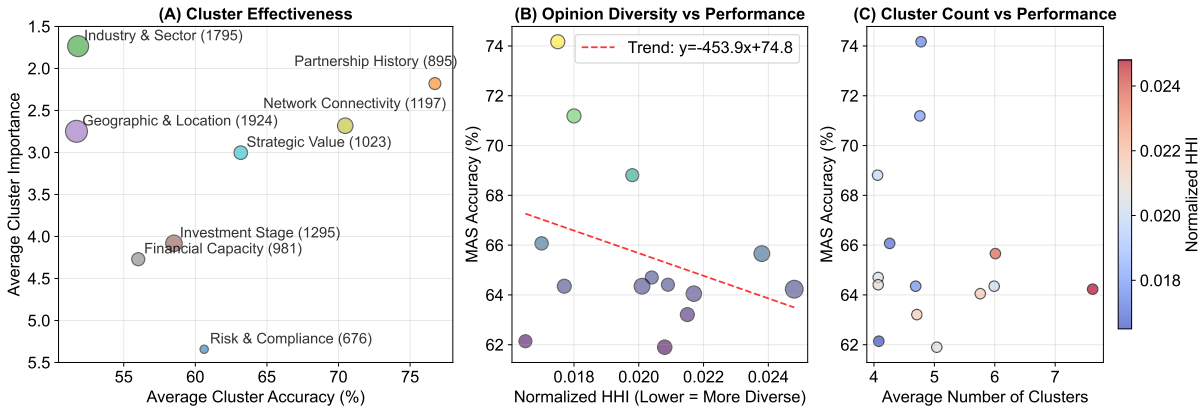

Figure 4: Agent performance grouped by Specialized Agent clusters. (A) Bubble chart of eight agent clusters, in which accuracy (x) vs importance rank (y, 1=highest), Bubble size = agents per cluster. (B) PARTNERMAS accuracy vs normalized HHI (lower = more diverse) with trend line. Node size = cluster count. (C) PARTNERMAS accuracy vs number of Specialized Agent clusters.

Network Connectivity Agents tend to be among the strongest performers, while Industry and Geographic Agents are often ranked highly by the Planner/Supervisor Agent despite lower accuracy. This misalignment implies that planning and supervision may overvalue broad topical coverage relative to historically effective co-investment signals. Subfigures (B) and (C) show that PARTNERMAS accuracy is highest when the number of active agents is modest (approximately 4–5), and opinion diversity is more concentrated (lower normalized HHI). As agent count and heterogeneity grow, returns diminish and aggregation becomes harder, suggesting that excessive diversity can dilute the Supervisor's ability to extract a coherent signal.

Model choice and business-domain-guided prompt drive planning. Table 2 reveals that the Planner's decisions are most significantly influenced by its core instructions and backbone LLM rather than specific case context. The backbone LLM and the inclusion of a business-domain guidance are overwhelmingly the strongest predictors for the type and number of agents deployed. For example, the odds of deploying an "Industry & Sector" agent increase by a factor of 57.61 when a business-domain guidance is provided. In contrast, for most cases, the contextual factors, such as the target company's industry focus or geolocation, show no statistically significant effect. This indicates that the Planner Agent operates at a strategic level, relying on its guiding prompts and model architecture to structure the problem-solving approach, rather than the case details.

Specialized Agents value different features and their performance varies. To make dynamically generated specialist roles comparable across cases, we map each generated agent profile to an embedding-derived cluster and then aggregate both its selected feature mentions and its shortlist accuracy within that cluster. As illustrated in Figure 5, the effectiveness of Specialized Agents highly depend on their assigned role, leading to significant performance variations across areas of expertise. For instance, when using the gpt-4.1-mini backbone, the "Risk & Compliance" Agent excels with 83.3% accuracy, while the Investment Stage" Agent struggles, achieving only 37.7%. Similar gaps appear with other models, though those driven by gpt-5-nano exhibit noticeably lower variance.

This performance difference is probably because how agents, guided by their roles, focus on different features. Agents can successfully identify and prioritize relevant information; for example, the Geographic & Location" Agent correctly emphasizes "geography_preference" and "location" features. Interestingly, the underlying LLM shapes the agent's reasoning style. The "gpt-4.1-mini" model demonstrates a direct focus on specific features, with the Industry & Sector" Agent targeting firm industry focus and the "Network Connectivity" Agent concentrating on tie strength, degree, and bonacich centrality. In contrast, the gpt-5-mini model displays a more distributed pattern, as Planner Agent driven by gpt-5-mini or -nano tends to generate a larger number of Specialized Agents, whose abilities may overlap. However, this broader agent deployment does not translate to superior performance, with gpt-5-nano-driven clusters not exceeding 70% accuracy. This trend is also observed for gpt-5-mini, despite a standout 92.5% accuracy from its "Partnership History" Agent cluster.

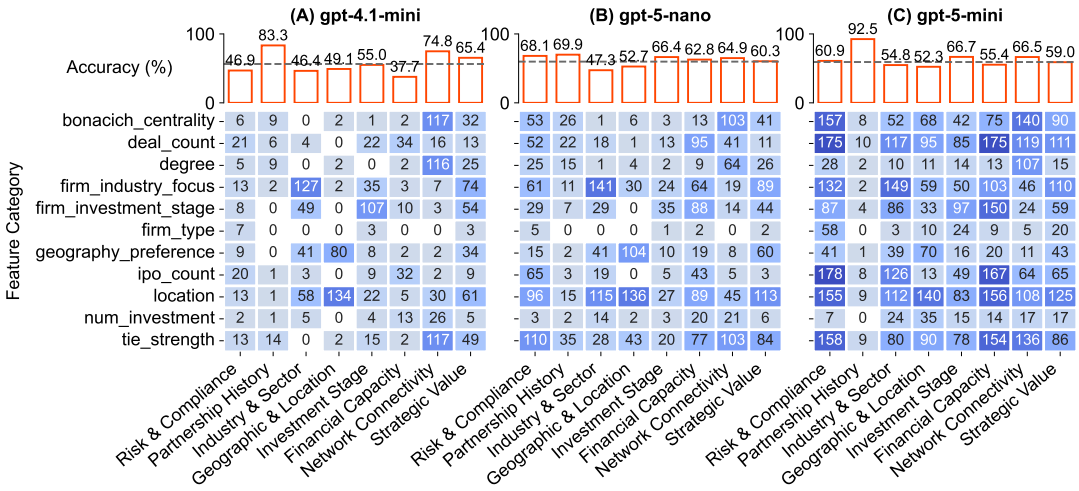

Figure 5: Accuracy and feature focus of Specialized Agents under different backbones: (A) gpt-4.1-mini. (B) gpt-5-nano. (C) gpt-5-mini.

Table 2: Planner Agent deployment regression analysis with label encoder.

Variable	Agent Presence (Logistic Regression - Odds Ratios)								Agent Count
	Risk & Compliance		Industry & Sector		Financial Capacity		Strategic Value		Linear Regression
	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.	Coef. (SE)
prompt_hint	23.06	***	57.61	***	2.49	***	1.16	n.s.	0.12** (0.05)
model	141.94	***	0.55	***	2.47	***	6.52	***	0.95*** (0.02)
company_state	1.02	n.s.	1.00	n.s.	1.02	n.s.	0.99	n.s.	-0.00 (0.00)
company_industry	0.71	*	1.01	n.s.	0.91	n.s.	1.09	n.s.	-0.03 (0.03)
firm_investment_stage	1.02	n.s.	1.00	n.s.	0.96	*	1.00	n.s.	-0.00 (0.01)
firm_type	0.88	n.s.	1.16	*	1.05	n.s.	0.88	n.s.	-0.01 (0.02)
geography_preference	0.98	n.s.	1.00	n.s.	0.97	***	1.03	**	-0.00 (0.00)
firm_state	0.99	n.s.	1.01	n.s.	0.98	n.s.	0.99	n.s.	0.00 (0.00)
firm_industry_focus	0.99	n.s.	1.01	n.s.	1.01	n.s.	1.02	n.s.	-0.00 (0.00)
R^2	0.711		0.302		0.181		0.361		0.664

Notes: prompt_hint (generic = 0; business = 1). model (gpt-4o-mini = 0; gpt-4.1-mini = 1; gpt-5-nano = 2; gpt-5-mini = 3). Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. $p \geq 0.05$. Other four Specialized Agent clusters do not show any significance and therefore are not presented in this table.

6 Discussion

Our work makes three key contributions. First, we introduce a benchmark dataset for evaluating LLMs on high-dimensional tabular problems that combine numerical, textual, and categorical attributes. Grounded in real VC co-investment records, the dataset provides a realistic setting for testing whether models can recover historical shortlisting behavior in structured business decisions. Second, we propose PARTNERMAS, a hierarchical MAS that decomposes complex evaluation into planner, specialist, and supervisor layers. Unlike single-agent or debate-based MAS approaches, PARTNERMAS dynamically configures role-specialized agents, asks them to focus on different feature subsets, and coordinates their outputs through explicit aggregation. Third, our analyses reveal transferable design patterns: planners are shaped strongly by prompts and backbones, moderate role diversity works better than excessive agent proliferation, specialized agents provide complementary feature coverage, and supervisor aggregation is a critical bottleneck.

These findings suggest that structured collaboration among LLM agents can outperform both single-agent and debate-based MAS baselines for high-dimensional shortlisting tasks. At the same time, the benchmark should be interpreted as measuring alignment with observed historical partner selections, not the optimality of those selections. VC syndication can depend on private relationships, timing, trust, and negotiation factors that are only partially captured by observable features. Therefore, PARTNERMAS is best viewed as a decision-support framework for generating interpretable candidate shortlists rather than an autonomous investment decision system. Future work should validate the design in additional structured matching domains and incorporate richer outcome or expert-evaluation signals when available.

Limitations

This study presents several opportunities for future work. First, the dataset only has 140 cases due to availability and quality constraints, and its exclusive focus on U.S. venture capital restricts geographic and institutional diversity. While our sensitivity analysis (see Appendix E) confirms that performance estimates are stable across sample sizes, the findings may not generalize to other national contexts where regulatory frameworks, market structures, and investment norms differ substantially. Additionally, the reliance on historical co-investment records means that the ground truth reflects past syndicate formation, which may not fully capture evolving partnership criteria or emerging investment strategies. Future work could expand the benchmark to include cross-border syndicates, or alternative partnership contexts such as strategic alliances and joint ventures, thereby testing the robustness across a broader range of scenarios.

In addition, our evaluation mainly relies on GPT models, leaving open how the system performs with lighter-weight or open-source models that would be more practical in privacy-sensitive environments. Furthermore, the Supervisor Agent occasionally aggregates their outputs suboptimally, reducing final shortlist quality. Examples of failure cases are presented in Appendix M. This suggests that final aggregation is the performance bottleneck. Improving supervisory mechanisms through techniques such as meta-reasoning or structured consensus protocols represents a key direction for future research.

Ethical Considerations

We adhere to the Code of Ethics and conducted this study using company- and firm-level investment records from licensed sources (e.g., LSEG Workspace (London Stock Exchange Group, 2024) and PitchBook (PitchBook Data, Inc., 2024)). The research does not involve human subjects or personally identifiable information. Due to licensing and confidentiality constraints associated with these data sources, we do not redistribute the raw data; we report aggregated analyses in the paper, and the curated test dataset is available from the authors upon reasonable request for research purposes only.

PARTNERMAS is designed as a decision-support system that produces shortlists and rationales to assist expert judgment; it is not intended to autonomously make or execute investment decisions. As with any system trained or powered by large language models and historical records, outputs may reflect biases or limitations present in data and models. We do not claim to have performed formal fairness or bias audits in this work; instead, we acknowledge this as an important limitation and encourage careful human oversight in any practical use. We reduce variance where possible by using deterministic settings (*e.g.*, temperature set to 0; see Section 4.2) and by grounding prompts in domain-relevant factors (Appendix N). We also describe our use of LLMs for research assistance in the Appendix A.

Reproducibility Statement

We aim to make our study reproducible within the constraints of data licensing and LLM services. The problem setup, model architecture, and evaluation protocol are described in Section 3. Data construction and filtering steps for the candidate pool are detailed in Section 4.1, and the feature set is summarized in Appendix D. Experimental settings (including shared protocols and deterministic decoding with temperature set to 0) are provided in Section 4.2. The prompts used for each agent and configuration are included in Appendix N, including concrete versions for the Single Agent (Appendix N.2) and PARTNERMAS (Appendix N.4).

The code base for the project is available at this anonymous link. Our curated test dataset contains firm- and deal-level information subject to license and confidentiality obligations; to protect the privacy and commercial sensitivities of the companies involved, the dataset is available from the authors upon request for research purposes. The prompts necessary to reproduce the agent behaviors are appended at the end of the paper.

Due to the evolving nature of LLM services and provider-side updates, exact numerical results may exhibit minor variation across runs or over time, even with temperature set to 0. To mitigate this, we standardize the evaluation metric (Match Rate), use a fixed protocol across all experiments, and document all key choices in the paper and appendix so that researchers can follow the same setup and compare results under similar conditions.

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A Use of LLMs

During the development of this paper, we use LLM Assistants in the following aspects: (i) Reference discovery: use the deep research tools from major providers to explore relevant work and literature. (ii) Code assistance: use coding agents to assist developing the code base of the current work. (iii) Grammar check: use LLMs to detect grammar errors in the drafty version of the paper, for better displaying our results.

B Data Availability

This curated dataset offers a reliable foundation, as both LSEG (London Stock Exchange Group, 2024) and PitchBook (PitchBook Data, Inc., 2024) provide clear, consistent records of first-round investments and designated lead VCs, which allows researchers to cross-verify records. While licensing restrictions prevent us from sharing the raw data publicly, it is available for research purposes upon reasonable request to the corresponding authors.

C Relation to MAS and Tabular LLMs

MAS frameworks. Recent MAS frameworks explore ways for improving agent performance. MAS-ZERO introduces a self-evolving architecture that generates and refines agents during inference rather than assigning roles upfront (Ke et al., 2025). Conversely, "More Agents is All You Need" shows that scaling homogeneous agents with aggregation or voting can improve performance without requiring explicit coordination (Li et al., 2024a). Debate-based MAS, such as Multi-Agent Debate (Liang et al., 2024) and ChatEval (Chan et al., 2024), rely on adversarial critique to refine responses. Other representative systems include CAMEL, which applies role-playing communication (Li et al., 2023); MetaGPT, which encodes standardized operating procedures for specialized roles (Hong et al., 2023); and AgentVerse, which performs dynamic expert recruitment based on task context (Chen et al., 2024). These mas frameworks emphasize scale, adaptivity, or debate-driven refinement as mechanisms for improving reasoning.

LLMs for tabular data reasoning. A parallel line of work shows that LLMs can handle high-dimensional structured data through language-based interpretation of feature names and metadata. Single-agent approaches such as LLM-Select (Jeong et al., 2024) and LLM-LASSO (Zhang et al., 2025) leverage pretrained knowledge to identify important predictors or guide traditional statistical selection methods, often without additional training.

How PARTNERMAS differs. PARTNERMAS proposes a hierarchical and domain-guided MAS specifically designed for high-dimensional decision-making. Unlike prior MAS structures, PARTNERMAS uses a Planner–Specialist–Supervisor workflow that decomposes the high-dimensional challenge into domain-relevant dimensions and coordinates expert agents. This design strengthens theoretical foundations for MAS in tabular contexts by showing that guided division of labor and principled aggregation can be more effective and interpretable than either fully adaptive or purely scale-driven systems.

D Feature Description

For each company's lead investor, we extract the relevant subset of potential coinvestors from the VC pool based on the company's industry, headquarter state, and the first-round investment year. We then construct pairwise lead VC–VC firm observations to capture prior co-investment experiences (Bellavitis et al., 2020) and geographic distance between partners (Sorenson and Stuart, 2001; Gulati et al., 2012). In addition to these network measures, we obtain detailed firm-level characteristics from LSEG Workspace (London Stock Exchange Group, 2024), including firm location (county and state) and investment preference variables such as geographic, industry, and stage preferences. These additional attributes allow us to account for both structural and preference-based drivers of syndicate partner selection, as illustrated in prior studies (Hsu, 2004; Gulati et al., 2012). Detailed description of features for VC firms is presented in Table 8.

E Sample Size Justification

Multiparty alliance datasets are inherently challenging to compile at large scale. Compared to dyadic partnerships, multiparty settings experience substantially higher rates of missing or incomplete records. Sample sizes similar to ours are standard in top-tier business and management research venues. For example, Lioukas and Reuer (2020) analyze 119 R&D alliances; Gong et al. (2007) study 224 multiparty international joint ventures; and Kim and Park (2021) evaluate 374 VC syndicates, though without the detailed structural, relational, and geographic attributes required for partner selection modeling.

Table 3: Sample size sensitivity analysis (Match Rate reported as mean ± 95% confidence interval).

Sample Size	gpt-o3-nano (mean ± 95% CI)	gpt-4.1-mini (mean ± 95% CI)
50	64.70 ± 3.75	71.32 ± 4.01
60	64.22 ± 3.36	71.10 ± 3.56
70	64.51 ± 2.53	71.57 ± 3.01
80	64.19 ± 2.48	70.93 ± 2.79
90	64.18 ± 1.86	71.30 ± 1.93
100	64.16 ± 1.77	71.22 ± 1.76
110	64.12 ± 1.56	71.28 ± 1.54
120	64.33 ± 1.14	71.40 ± 1.33
130	64.24 ± 0.79	71.18 ± 0.86
140	64.35 ± 0.00	71.19 ± 0.00

Our original dataset is substantially larger, comprising 52,662 companies backed by 16,030 VC firms. However, strict criteria are required to ensure high-fidelity partner selection contexts: (i) complete first-round syndicate information, (ii) a single identifiable lead VC, and (iii) full relational and network data for that lead VC. Cases violating any criterion are excluded. While this yields 140 focal cases, the effective analytical scale is considerably larger: each case produces numerous pairwise lead–candidate evaluations within the same year–state–industry context, resulting in over 14,000 total comparisons. This provides a rich, high-dimensional evaluation structure beyond the case count alone. Detailed distributions of industries, investment stages, firm types, and geographic coverage are provided in Appendix F.

To further verify the reliability of our results, we conduct a sample-size sensitivity analysis, as shown in Table 3. As the sample size increases, accuracy remains highly consistent with narrowing confidence intervals. This demonstrates the stability of our findings and confirms that performance gains are robust rather than dependent on a small or specific subset of data.

F Data Distribution

Figure 6 shows the distribution of lead VC firms across four key characteristics in our compiled dataset. Panel (A) displays firm industry preferences, with High Tech (30 firms) and Software (25 firms) being the most common categories. Panel (B) presents investment stage preferences, where Early Stage (63 firms) represents the largest group, followed by Seed Stage (33 firms) and Balanced Stage (27 firms). Panel (C) illustrates firm type distribution, with Private Equity Firms (114 firms) comprising the majority of organizations. Panel (D) depicts the geographic distribution by state, showing California (62 firms) as the most represented location, followed by New York (16 firms) and Massachusetts (13 firms).

G Agent clusters

In the PARTNERMAS workflow, for each experimental setting, the Planner Agent is prompted to generate a set of Specialized Agents. Specifically, it produces a list of profiles, one for each agent. Each profile specifies four elements: (i) agent name, (ii) role, (iii) abilities, and (iv) guides. Across all 14 experimental settings using the PARTNERMAS framework, a total of 9,786 profiles are generated. Since agent names can vary slightly across settings, grouping by name alone would yield an excessive number of fragmented clusters. To address this, we cluster agents using embeddings so that those within the same cluster share similar profiles, whether in roles or guides emphasizing comparable features of candidate VC firms.

The clustering process proceeds as follows. First, we use an embedding model "all-MiniLM-L6-v2" to create one profile vector for each specialized agent. Second, we use the "k-means" clustering method to aggregate all agents. After experiments on the number of clusters, we find that $k = 8$ (i.e. eight clusters) balances the cluster size, similarity within clusters, and diversity between clusters, and achieve an acceptable Silhouette score at 0.290. As a result, we obtain eight clusters for all 9,786 agent names among 14 test experimental setting.

H Debate MAS Design

The Debate MAS enhances decision quality through structured multi-phase interaction among agents. Instead of relying on a single evaluation, the system encourages critique, reflection, and oversight, leading to more robust outcomes.

- **Evaluation Phase:** Each agent independently evaluates the candidate firms, producing initial scores and rationales.
- **Debate Phase:** Agents review their peers' reasoning (not the scores) and provide agreements, disagreements, and clarifying questions. This peer-review process emphasizes justification quality and helps surface biases or overlooked factors.
- **Reflection Phase:** After the debate, each agent revisits its own evaluation in light of peer feedback, reflecting critically and optionally adjusting its decisions.

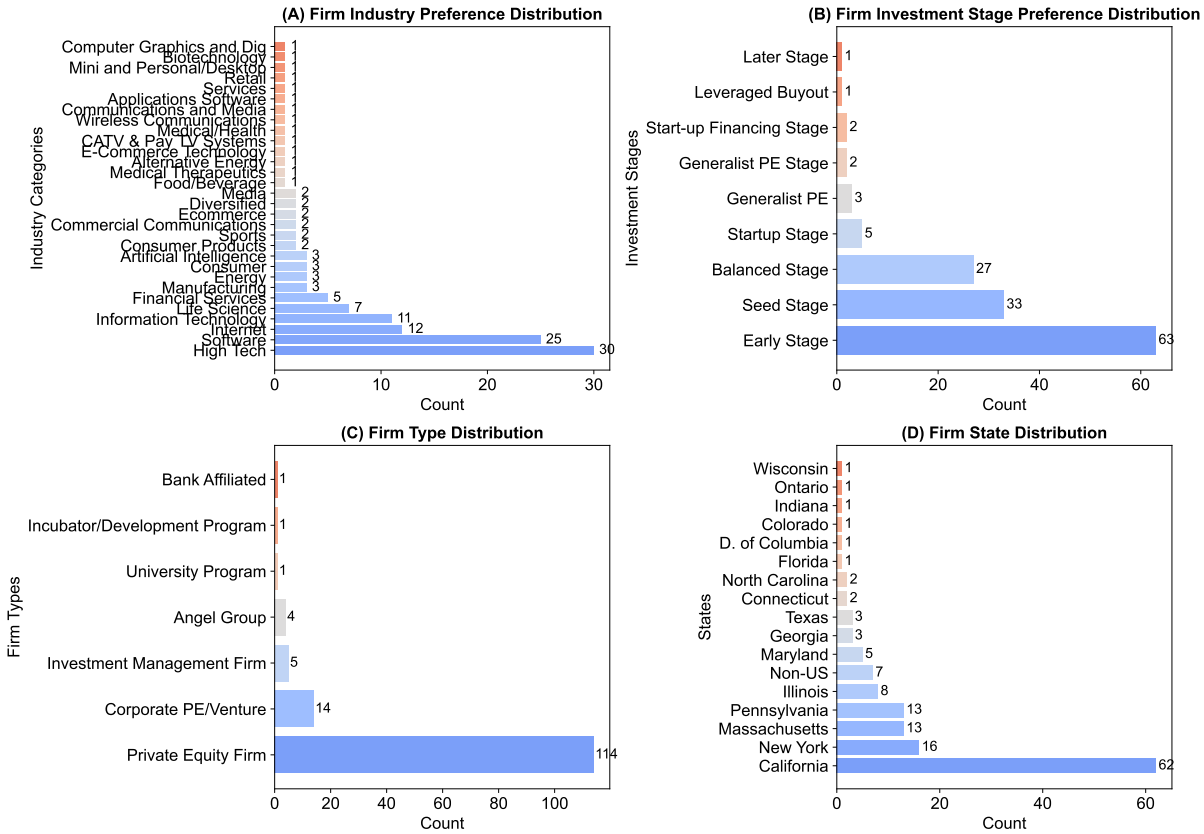

Figure 6: Distribution of lead VC firm across four key dimensions. (A) Firm industry preference. (B) Firm investment stage preference. (C) Firm type. (D) Firm geographic location by state.

In the end, a dedicated Supervisor Agent integrates the outcomes from all phases, resolves conflicts, and produces the final decision. The supervisor focuses on synthesizing insights across agents rather than simple score aggregation.

I Additional Evaluation Metrics

Retrieval-Based Metrics (Accuracy, Recall, Precision, F1). Our task is formulated as a fixed-size shortlist retrieval problem. In practice, our setup follows a common business shortlisting heuristic where the ground-truth co-investor set, the shortlist, and the initial candidate pool follow an approximate 1:3:9 layering structure. Concretely, for each case, if the ground-truth syndicate has $|G|$ firms, the candidate pool size is roughly $9|G|$, and the shortlist size is $3|G|$. This yields the relation that $k = |C|/3$, where $|C|$ is the entire number of candidates. Under this fixed-ratio design, all retrieval metrics become tightly coupled:

$$\text{Match_rate} = \text{Recall} = |S \cap G|/|G| \quad (2)$$

$$\text{Precision} = \frac{|S \cap G|}{|S|} = \frac{|S \cap G|}{3|G|} = \frac{\text{Recall}}{3} \quad (3)$$

Therefore, precision, recall, and F1 score do not provide different conclusions—they follow the same result. This is why Match Rate is fully representative of retrieval performance in our setup.

Ranking-Based Metrics (MRR, nDCG@3, nDCG@5). Our primary formulation treats business partner selection as a retrieval task, where the goal is to correctly include the true co-investors in the shortlist regardless of order. In real VC workflows, shortlisting is set-based; the list is typically handed to human experts, and the final decisions depend on expert review rather than the internal ranking produced by an automated system. However, as our system outputs a list rather than an unordered set, we report ranking-based metrics, including MRR, nDCG@3, and nDCG@5 as complementary measures. These ranking metrics exhibit the same performance trends as our retrieval metrics, and they further confirm the advantage of PARTNERMAS over alternative baselines. Results are presented below.

J Comparison with ML Models

To provide a comprehensive evaluation, we compare PARTNERMAS against both supervised and unsupervised machine learning baselines.

Supervised Methods. All supervised models follow an 80/20 train-test split. (i) **Random Forest**:

Table 4: Retrieval and ranking performance across three LLM backbones.

Backbone	Setting	Match Rate	MRR	nDCG@3	nDCG@5
gpt-o3-mini	Single – w/o domain guide	54.8%	0.455	0.265	0.318
	Single – w. domain guide	57.2%	0.472	0.279	0.330
	Debate – w/o domain guide	56.5%	0.530	0.360	0.405
	Debate – w. domain guide	58.4%	0.555	0.345	0.395
	PARTNERMAS– w/o domain guide	63.2%	0.554	0.392	0.437
	PARTNERMAS– w. domain guide	**64.2%**	**0.541**	**0.342**	**0.391**
gpt-4o-mini	Single – w/o domain guide	55.5%	0.458	0.277	0.334
	Single – w. domain guide	57.8%	0.450	0.283	0.348
	Debate – w/o domain guide	55.3%	0.505	0.340	0.385
	Debate – w. domain guide	58.9%	0.545	0.365	0.420
	PARTNERMAS– w/o domain guide	61.9%	0.524	0.361	0.406
	PARTNERMAS– w. domain guide	**64.4%**	**0.525**	**0.353**	**0.414**
gpt-4.1-mini	Single – w/o domain guide	56.0%	0.505	0.311	0.355
	Single – w. domain guide	61.0%	0.553	0.346	0.392
	Debate – w/o domain guide	59.1%	0.565	0.395	0.435
	Debate – w. domain guide	64.9%	0.630	0.440	0.490
	PARTNERMAS– by importance w/o domain guide	66.1%	0.585	0.422	0.453
	PARTNERMAS– by importance w. domain guide	71.2%	0.654	0.461	0.509
	PARTNERMAS– by majority w. domain guide	**74.2%**	**0.641**	**0.455**	**0.493**

Notes. Match Rate corresponds to recall in our fixed-ratio retrieval setup. MRR, nDCG@3, and nDCG@5 are complementary ranking metrics. Best results per model are in **bold**.

An ensemble of decision trees that learns feature-based decision rules and predicts co-investor probability by averaging outputs across all trees. (ii) **Logistic Regression**: It uses L2-regularized maximum likelihood estimation to learn model coefficients and predict co-investor probability for each candidate VC.

Unsupervised Methods. Unsupervised models in our study include: (i) **KNN (Euclidean)**: Ranks candidates based on Euclidean distance to the lead VC in feature space, where smaller distances indicate greater similarity. (ii) **Cosine Similarity**: Ranks candidates by the cosine similarity of their feature vectors to the lead VC, where higher values indicate closer matches. (iii) **K-Means Clustering**: Partitions VCs into clusters and selects candidates from the same cluster as the lead VC.

Table 6 presents the comparison results. PARTNERMAS demonstrates several key advantages over traditional ML methods: (i) Zero-Shot Operation. Unlike supervised methods that require training data, PARTNERMAS operates in a zero-shot manner. This is particularly valuable in real-world scenarios where firms often cannot access other VCs' historical investment data due to confidentiality constraints. (ii) Competitive Retrieval Performance. The best PARTNERMAS configuration (*gpt-4.1-mini* by majority, 74.2%) achieves match rates comparable to supervised methods while significantly outperforming unsupervised approaches. This demonstrates that LLM-based reasoning can capture complex co-investment patterns without explicit feature engineering or historical training examples. (iii) Superior Ranking Quality. PARTNERMAS outperforms all ML baselines on ranking metrics (MRR and nDCG@3), indicating better quality in top-ranked recommendations. (iv) Interpretable Reasoning. LLM agents provide natural language explanations for their recommendations, unlike black-box ML models, an important consideration for real-world investment decision-making.

K Supervisor Agent Strategy Analysis

As described in Section 3, the Supervisor combines consensus signals (candidates supported by multiple agents) with importance-weighted conflict resolution (e.g., prioritizing Industry & Sector over Geographic proximity when strategic fit dominates). In addition, we evaluate two alternative strategies for robustness analysis. In the Majority Vote strategy, the Supervisor directly selects candidates based on aggregate support across all Specialized Agents. In the By Weight strategy, the Supervisor assigns explicit weights to each Specialized Agent and determines the final decision by applying these weights to candidate scores.

Table 5 presents a controlled comparison using the same evaluation setting (`gpt-4.1-mini` backbone with business guidance) while varying only the Supervisor strategy. One notable finding is that simpler approaches tend to perform better: when the Supervisor directly aggregates outputs without complex weighting, overall performance is the highest. The "By Importance" strategy provides

Table 5: Comparison of Supervisor aggregation strategies. All experiments use gpt-4.1-mini with bus. guide.

Strategy	Match Rate	MRR	nDCG @3	nDCG @5
By Importance	71.2%	**0.654**	**0.461**	**0.509**
By Majority	**74.2%**	0.641	0.455	0.493
By Weight	64.4%	0.561	0.398	0.450

strong and consistent performance while preserving interpretability, as decisions reflect clearly articulated business priorities. Majority Vote yields slightly higher match rate but lacks transparency and is more susceptible to noisy Specialist populations. "By Weight" underperforms due to weight-estimation noise.

L Supervisor Agent "By Importance" Strategy Analysis

Table 7 shows the Supervisor Agent's "By Importance" strategy analysis. We find that prioritizing the right expert can increase the whole system performance. The regression analysis in Table 7 investigates how the Supervisor's ranking of agent importance correlates with the final match rate. For the gpt-5-nano backbone, assigning the top rank to the "Partnership History," "Industry & Sector," or "Geographic & Location" agent is a highly significant predictor of a correct final outcome ($p < 0.001$). For gpt-4.1-mini, success is strongly correlated with prioritizing agents on "Investment Stage" ($p < 0.001$), "Strategic Value" ($p < 0.01$), and "Network Connectivity" ($p < 0.01$). This highlights that the Supervisor's ability to weigh expert opinions is a key determinant of the system's performance. Even if individual Specialized Agents perform well, an error in prioritization by the Supervisor can lead to a suboptimal final shortlist.

M Failure Case Analysis

We present two representative failure cases to illustrate the limitations of PARTNERMAS.

Case A: The Conventional Excellence Trap Case A represents a scenario where PARTNERMAS performs poorly. Across 14 test rounds, the system achieved 50% accuracy in one round and 100% in another, with complete failure in the remaining 12 rounds. In 5 rounds, none of the specialized agents identified any real co-investors. The system struggles because three local IT-focused VCs dominated agent rankings, each being selected over 70 times. These firms represent the textbook "ideal co-investor" profile: located within 30 miles of the target company, matching industry focus and investment stage preferences, strong track records, and prior collaboration with the lead investor.

However, the real co-investors are statistically unlikely choices, a corporate VC located nearly 3,000 miles away with a Robotics focus and only 3 prior deals, and a PE firm over 1,000 miles away with an Industrial Products focus and only 2 prior deals. Both brought strategic industrial value that remains invisible to standard quantitative metrics. Meanwhile, superficially attractive candidates with impressive metrics but misaligned strategic fit blocked real co-investors from shortlists. Success depended heavily on agent composition: with Strategic Value agents included, real co-investors were identified 50–100% of the time; without them, success dropped to nearly 0%.

Case B: Supervisor Aggregation Failure Case B represents a scenario with misalignment between specialized agents and the supervisor. Across 14 test rounds, at least two specialized agents identify at least one real co-investor in 13 rounds. Yet in one notable failure, three agents identify real co-investors but the supervisor still fails to include any. The system succeeds in only a single round. The failure occurs because although real co-investors appeared frequently in agent shortlists, they are almost exclusively ranked at lower positions while other strong candidates dominated the top. When aggregating recommendations, the supervisor biases toward highly-ranked candidates, overlooking lower-ranked real co-investors.

Both cases suggest that real-world investment decisions do not always follow statistical patterns. These findings indicate two directions for future work: guiding specialized agents to recognize latent strategic value beyond statistical patterns, and developing supervisor aggregation mechanisms that better identify underweighted candidates.

Table 6: Comparison with traditional ML methods.

Method	Match Rate	MRR	nDCG@3	nDCG@5
Supervised Methods (28 cases)				
Logistic Regression	74.4%	0.485	0.419	**0.542**
Random Forest	**74.7%**	**0.506**	**0.421**	0.538
Unsupervised Methods (140 cases)				
KNN (Euclidean)	28.1%	0.273	0.125	0.147
Cosine Similarity	**42.1%**	**0.348**	**0.175**	**0.230**
K-Means Clustering	31.0%	0.289	0.142	0.173
PARTNERMAS *(140 cases)*				
gpt-4.1-mini (importance)	71.2%	**0.654**	**0.461**	**0.509**
gpt-4.1-mini (majority)	**74.2%**	0.641	0.455	0.493
gpt-o3-nano (importance)	64.4%	0.602	0.408	0.448

Notes. Supervised methods use 28 test cases (80/20 split); unsupervised methods and PARTNERMAS use all 140 cases. Best results per category are in **bold**.

Table 7: Regression analysis of Supervisor Agent's ranking.

Variable	gpt-4.1-mini	gpt-4o-mini	gpt-5-nano
R1_Risk & Compliance	-	-	-40.38
R1_Partnership History	7.29	21.15	20.33***
R1_Industry & Sector	2.39	16.04	23.44***
R1_Geographic & Location	20.21*	32.78	20.10***
R1_Investment Stage	22.43***	-	13.59
R1_Network Connectivity	11.98**	-	20.69***
R1_Strategic Value	19.35**	-15.21	13.59
R2_Risk & Compliance	-	-	45.60
R2_Partnership History	50.84	19.41*	4.70
R2_Industry & Sector	14.32*	38.72	10.56**
R2_Geographic & Location	8.22	21.18**	14.08***
R2_Investment Stage	15.39*	-	2.74
R2_Financial Capacity	-32.64	-44.54	-6.39
R2_Network Connectivity	19.11**	-	6.58
R2_Strategic Value	8.42	20.00	-6.53
prompt_hint_business	46.77***	28.50	33.71***
prompt_hint_generic	36.89***	25.00	37.64***
R^2	0.040	0.034	0.057

Notes. prompt_hint_business (yes = 1; no = 0). prompt_hint_generic (yes = 1; no = 0). Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

N Prompt Design

N.1 Business Domain Guidance

We include the following business domain guidance to ensure that agents explicitly consider factors such as collaboration history, industry fit, strategic alignment, financial strength, and geographic proximity when making investment decisions:

```
Your decision should consider important dimensions like network and collaboration history (pair tie
    strength with the lead company and boncent), industry fit (firm industry preference), strategic
    alignment (firm investment stage preference), financial, and geography (distance, firm state).
    Your strategic guidance should explain which of these dimensions are most critical for this
    specific deal.
```

N.2 Prompt for Single Agent

```
You are '{self.name}', {self.role}, possessing {self.ability}.

# Your Profile: {self.profile}

# Business Hint: (when enabled)
Your decision should consider important dimensions like network and collaboration history
(pair tie strength with the lead company and boncent), industry fit (firm industry preference),
```

```
strategic alignment (firm investment stage preference), financial, and geography (distance, firm
    state).
Your strategic guidance should explain which of these dimensions are most critical for this specific
    deal.

# Investment Target Company: {target_profile}

# Lead Investor Profile: {lead_profile}

# Candidate Co-Investors to Evaluate: {candidates_list}

# Evaluate candidates across different dimensions based on the agent expertise and profile.

# Scoring Guidance (1-5 scale):
- 1: Poor match, significant concerns, not recommended at all
- 2: Below average, considerable issues, generally not favorable
- 3: Average neutrality, acceptable but with clear reservations
- 4: Good candidate, strong fit with minimal concerns
- 5: Excellent candidate, ideal investment partner and highly recommended

# Task:
Evaluate each candidate and select the top {top_k} co-investors for this investment opportunity.
```

N.3 Prompt for Debate MAS

Stage 1: Initial Evaluation Prompt

```
You are '{self.name}', {self.role}, possessing {self.ability}. Evaluate the following candidates for
    potential investment:

# Scoring Guidance (1-5 scale)
- 1: Poor match, significant concerns, not recommended at all.
- 2: Below average, considerable issues, generally not favorable.
- 3: Average neutrality, acceptable but with clear reservations.
- 4: Good candidate, strong fit with minimal concerns.
- 5: Excellent candidate, ideal investment partner and highly recommended.

# Investment Target: {target_profile}

# Your Own Profile: {self.profile}

# Candidates to Evaluate: {candidates_data}

# Additional Context: {context}

# Evaluation to be strictly JSON formatted:
{
  "evaluations": {
    "firm_id_1": {
      "integrity_score": int (1-5),
      "integrity_rationale": "... clear rationale why this score was given ...",
      "capability_score": int (1-5),
      "capability_rationale": "... clear rationale why this score was given ...",
      "fit_score": int (1-5),
      "fit_rationale": "... clear rationale why this score was given ..."
    },
    "firm_id_2": {
      // ... same structure for each firm
    }
  }
}
```

Stage 2: Reflection Prompt

```
You are '{self.name}', ({self.role}). After reviewing your evaluations:

Evaluations: {evaluations}

Context: {context}
```

```
Reflect critically on the evaluations. Provide clear thoughts in strictly JSON:
{
"reflection_summary": "... comprehensive reflection on possible biases, assumptions, or key insights
    ...",
"improvement_suggestions": ["clear suggestions on improvement", "... more thoughtful suggestion"],
"score_decisions": {
   "reasoning": "... your explicit self-reflect reasoning clearly ...",
   "stick_with_previous_score": true|false
}
}
```

Stage 3: Debate Prompt

```
You are '{self.name}' ({self.role}). You are reviewing evaluations written by your peer agents.

IMPORTANT:
- You are debating with OTHER AGENTS about their evaluations, not with the firms being evaluated
- The numeric scores from your peers are intentionally hidden
- Focus ONLY on their reasoning and justifications not the scores
- You are reviewing ONLY your peers' evaluations, not your own
- The supervisor's evaluations are not included in this debate

Available peer agents to debate with: {peers_list}

All Agents' Evaluations (scores hidden):
{stripped_evaluations}

Context: {context}

Your task:
- Critically analyze the reasoning about the firms from other agents
- For each peer agent's evaluation, you can:
  * Agree with multiple points they made about a firm
  * Disagree with multiple points they made about a firm
  * Agree with some parts while disagreeing with others
- If something is unclear, ask specific questions directly to the relevant agent

Output as strictly formatted JSON:
{
  "agree": [
    {
      "agent_name": "name of the peer agent from available peer agents",
      "points": [
        "specific points you agree with about their evaluation",
      ]
    }
  ],
  "disagree": [
    {
      "agent_name": "name of the peer agent from available peer agents",
      "points": [
        "specific points you disagree with about their evaluation",
      ]
    }
  ],
  "questions": ["concise question directed clearly to agent_name about their evaluation"]
}
```

N.4 Prompt for PARTNERMAS (Ours)

Planner Agent Prompt

Generic

```
You are '{name}', a {role} with {ability}.
Your task is to design a multi-agent system for evaluating potential co-investor partnerships.
Based on the provided lead investor profile, target company profile and a sample of candidate co-
    investor profiles,
determine the optimal number of specialized agents, their specific roles, abilities, and profiles.
```

```
The goal is to create agents that can thoroughly evaluate candidates across different, relevant
    dimensions to find the best co-investors for the lead firm.
```

Business-Domain-Guided

```
You are '{name}', a {role} with {ability}.
Your task is to design a multi-agent system for evaluating potential co-investor partnerships.
Based on the provided profiles, determine the optimal specialized agents across different dimensions
(e.g., collaboration history, industry fit, strategic alignment, financial, geography, integrity) and
     formulate a high-level strategic guidance for the final decision-maker.

# Lead Investor Profile: {lead_profile}

# Investment Target Profile: {target_profile}

# Sample Candidate Co-investor Profiles (structure overview):
{sample_candidates}
(Note: This is just a sample of 2 candidates, infer general dimensions from the structure and target
    profile.)

# Your output MUST be a JSON object with TWO top-level keys: "strategic_guidance" and "agents".
# 1. "strategic_guidance": A concise paragraph outlining the most critical factors for selecting a co
    -investor for THIS SPECIFIC target. This is high-level advice for the supervisor.
# 2. "agents": A JSON array of agent configurations. Each agent must have a distinct profile that
    covers a key evaluation criterion inspired by the strategic guidance.
```

Specialized Agent Prompt

```
You are '{name}', a {role} with {ability}.
Your specific focus is: {profile}.

# Investment Target: {target_profile}

# Candidates to Evaluate: {candidates_data}

Your task is to identify and rank the **top {dynamic_top_k}** most suitable candidate co-investor
    companies from the total of {total_candidates} candidates for the investment target.
Focus specifically on your area of expertise as defined in your profile using a clear logical flow:
# 1. **Select Focus:** State the key features you will focus on.
# 2. **Formulate Overall Strategy:** Explain your overall reasoning and methodology based on that
    focus.
# 3. **Make Decisions:** Rank the top candidates according to your focus and reasoning.

# Your Output MUST be a JSON object with THREE top-level keys in this specific order:
  - "evaluation_focus": A concise string identifying important features you are using for your
      analysis.
  - "overall_rationale": A general explanation of your ranking methodology, consistent with your
      stated focus.
  - "ranked_candidates": A list containing *exactly* the top {dynamic_top_k} candidates. Each
      rationale in this list must be a direct result of applying your focus and overall rationale.
```

Supervisor Agent Prompt

Co-investor Selection by Importance

```
You are '{name}', {role}, and you have the final say on co-investor selection.
Your goal is to produce a final, ranked shortlist of exactly **{top_k}** candidates.

# Strategic Guidance from Planner:
# This is the high-level strategy you must follow for this specific deal.
{planner_strategic_guidance}

# Your Decision-Making Process (Follow these steps precisely):
1. **Step 1: Identify Consensus Picks.**
    - Review all agent evaluations and identify candidates that are highly ranked by multiple agents.
    - Add the strongest consensus candidates to your shortlist first.
    - In your rationale, state how many consensus picks you found.

2. **Step 2: Fill Remaining Slots via Conflict Resolution.**
    - You now need to fill the remaining slots to reach the target of **{top_k}** candidates.
```

```
    - Examine candidates with mixed reviews (e.g., ranked high by one agent but low or not at all by
        another).
    - Use your Agent Importance Ranking as the decisive tie-breaker. The opinion of a more important
        agent carries significantly more weight.
    - Select the best of the remaining candidates based on this weighted analysis until your
        shortlist has exactly **{top_k}** members.
```

Co-investor Selection by Weight - Weight Assign Prompt

```
You are '{name}', {role}. Your goal is to make the best possible co-investor selection.
Before you review the candidate rankings from your specialized agents, you must first determine the
     numerical weight of each agent's perspective for this specific investment opportunity.

# Your Task:
Assign a numerical weight to each specialized agent based on how critical their focus is for this
     specific target. The weights must be a floating-point number (e.g., 0.35) and **the sum of all
     weights must equal 1.0**.
```

Co-investor Selection by Weight - Selection Prompt

```
You are '{name}', {role}, possessing {ability}. Your profile is: {profile}.
You are the General Partner and have the strongest voice in deciding who gets invited and joins the
     round.
Your task is to review the detailed evaluations from your specialized agents and, guided by the
     numerical weights you just assigned, make the final decision on the top {top_k} candidates for
     co-investment.

# Your Decision:
Based on all the information provided, and critically, *following the numerical weights you
     established*, select the best {top_k} candidates.
- For each candidate: Sum up the weights of all agents that recommended this candidate
- Final ranking: Order candidates by their total weighted scores from highest to lowest
```

Co-investor Selection by Majority Vote

```
 You are '{name}', {role}, possessing {ability}. Your profile is: {profile}.
You are the General Partner and have the strongest voice in deciding who gets invited and joins the
     round.
Your task is to review the detailed evaluations from your specialized agents and make the final
     decision on the top {top_k} candidates based on a **majority vote**.

# Your Decision:
Based on all the information provided, and select the best {top_k} candidates.
- Identify which candidates are most frequently recommended by the different agents.
- A candidate that appears on multiple agents' lists should be prioritized.
- Your final list should represent the collective decision from your team of agents.
```

Table 8: Key features used in VC co-investor shortlisting and their descriptions.

Feature	Type	Description
Identifiers & labels		
companyid	ID	Unique identifier of the target company in the focal deal.
vcfirmid	ID	Unique identifier of the candidate VC firm.
leadvc	ID	Identifier of the lead VC for the focal deal.
real	Binary	Ground-truth label: 1 if candidate VC appears in the actual syndicate; 0 otherwise.
leadornot	Binary	Indicator for whether the VC is the lead investor.
yearquarter	Categorical	Year–quarter context of the focal deal (e.g., 2019Q3).
year	Numeric	Calendar year of the focal deal.
realsize	Numeric	Number of ground-truth co-investors in the focal syndicate.
Target company attributes		
companyindustrymajorgroup	Categorical	Major industry grouping of the target company.
companynation	Categorical	Target company headquarters nation.
companystate	Categorical	Target company headquarters state (if applicable).
companycity	Categorical	Target company headquarters city.
companyzip	Categorical	Target company ZIP/postal code.
companylat	Numeric	Latitude of target company.
companylng	Numeric	Longitude of target company.
Candidate VC firm attributes		
firmtype	Categorical	Type of investor.
firmnation	Categorical	VC firm nation.
firmstate	Categorical	VC firm state (if applicable).
firmcounty	Categorical	VC firm county (if applicable).
firmzipcode	Categorical	VC firm ZIP/postal code.
firmgeographypreference	Text	Stated geographic investment preferences.
firmindustrypreference	Text	Stated industry/sector preferences.
firminvestmentstagepreference	Text	Stated stage preferences (e.g., seed, early, growth).
Candidate VC activity & outcomes (rolling/cumulative)		
vcfirm_dealcount_20qtr	Numeric	Deals by the VC in the past 20 quarters.
vcfirm_numcompinvest_20qtr	Numeric	Co-investments by the VC in the past 20 quarters.
vcfirmIPOcount_20qtr	Numeric	IPO exits associated with the VC in the past 20 quarters.
vcfirm_IPOcount_cum	Numeric	Cumulative IPO exits associated with the VC to date.
vcfirm_dealcount_cum	Numeric	Cumulative deals by the VC to date.
vcfirm_numcompinvest_cum	Numeric	Cumulative co-investments by the candidate VC to date.
Network measures & pairwise history		
boncent	Numeric	Bonacich centrality of the VC in the co-investment network.
degree	Numeric	Degree centrality in the co-investment network.
pair_tie_strength	Numeric	Prior collaboration strength with the lead VC.
Candidate VC geospatial		
uszip_vc	Categorical	U.S. ZIP code of the VC (normalized field, if applicable).
uslat_vc	Numeric	U.S. latitude of the VC office (normalized field).
uslng_vc	Numeric	U.S. longitude of the VC office (normalized field).
uscity_vc	Categorical	U.S. city of the VC office (normalized field).
uscounty_vc	Categorical	U.S. county of the VC office (normalized field).