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Mergers and Acquisitions Pricing Multi-agent Cross-Questioning: Paradigm Evolution and Framework

Yanlin Liang

College of International Science and Technology, Jinan University, Guangzhou, China
yanlinliang@stu2024.jnu.edu.cn

Abstract. This paper systematically reviews the evolution direction of financial artificial intelligence (AI) from traditional statistical fitting to dynamic confrontation. With the help of functional isolation, evidence-based game theory and parameter correction, this paper analyzes the internal law of the multi-agent cross-questioning mechanism, and summarizes a set of structured analysis frameworks. Relevant studies have shown that compared with a single model, the core purpose of building a specific questioning mechanism using confrontation topology is to get through the logic of transforming unstructured semantic risk into structured valuation parameters, to clearly depict the cross-modal mapping path between the two. This model has significant theoretical feasibility in improving the internal consistency of pricing logic and restraining unreasonable premiums. This paper believes that the dynamic inquiry paradigm is conducive to optimizing and reshaping the existing asset valuation benchmark in a complex trading environment. To truly land the man-machine collaborative pricing system, the core is to focus on how to resolve the technical barriers of reasoning interpretability, privacy protection, collaborative deduction and penetration algorithm audit. Only by achieving substantial breakthroughs in these bottlenecks can the follow-up system construction have a solid foundation.

Keywords: Mergers and acquisitions, multi-agent systems, large language models, cross-questioning, asset valuation

1. Introduction

Mergers and acquisitions (M&A) pricing is not a static valuation, but uses data under information asymmetry (IA) to dynamically target the fair value (FV) of assets [1, 2]. With the process of digitalization, this kind of data is huge and complex in dimensions, which has exceeded the processing limits of traditional models [2]. This environment often masks management's information manipulation in tone or semantics, which makes traditional quantitative methods difficult to identify [3]. This also fully confirms the shortcomings of traditional models, so it is urgent to introduce new paradigms [4]. Although the emergence of large language models (LLMs) can indeed process unstructured information, once the pricing with extremely high logical accuracy is reasoned, this structure is prone to logical fracture due to the lack of audit constraints, and even draw some absurd conclusions that completely deviate from financial common sense [5, 6]. Given the inherently rigorous nature of M&A valuations, every inference must withstand multiple rounds of falsification.

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Based on this demand, the research perspective is shifting from static analysis to a multi-agent architecture with cross-questioning ability [7, 8].

The evolution of this architecture actually redefines the form of communication between subjects. Through functional decoupling, different modules check and balance each other in position confrontation, so as to open up a self-calibrating falsification path under the guidance of evidence-game theory and dynamically correct the valuation premium. Based on the above background, this paper establishes a structured analysis framework to provide a new theoretical perspective for solving FV pricing in complex trading scenarios.

2. Paradigm evolution of AI-driven mergers and acquisitions pricing

2.1. Technological evolution and individual limitations

Traditional financial machine learning is mostly limited to structured data analysis, which will expose bottlenecks in the face of complex unstructured texts [2, 9]. The emergence of LLMs promotes the transition of data processing from feature engineering to a deep semantic layer, which can directly parse files. When dealing with tasks such as financial summary extraction, the model mainly relies on the built-in thinking chain and context correlation ability to complete logical deduction and trend representation [4]. This one-way workflow reduces the decision-making path and effectively meets the core demands of improving the efficiency of basic financial business and large-scale output.

However, in the M&A scenario involving high-level game, the monomer model has limitations [3, 10]. In order to overcome the bias of one-way reasoning, a multi-agent debate mechanism is introduced to realize independent evaluation and calibration of reasoning through heterogeneous collision [11]. M&A pricing involves conflicts of interest review rather than simple data integration [3, 12]. In this case, management uses tone manipulation to cover up business risks or improve valuation expectations, and puts forward extremely high requirements for model verification capabilities. Constrained by its endogenous autoregressive generation mechanism and one-way reasoning, it is easy to be biased by misleading information in the context of rhetorical analysis. Due to the lack of checks and balances on the objective function, the initial deviation will continue to enlarge with the reasoning chain, and eventually lead to output results breaking away from the underlying financial logic and losing the reference value of decision-making [5, 7]. The lack of this mechanism will inevitably promote the transformation of financial AI from a single agent model to a multi-agent confrontation topology. Introducing game mechanisms between subjects is expected to repair reasoning logic and restore financial analysis rigor [6, 8].

2.2. Multi-player cooperation and adversarial game

The introduction of multi-agent adversarial architecture aims to build a restraint mechanism for M&a pricing [4, 12]. This architecture replaces single computing logic through structured games, thus giving the valuation model the ability to self-correct. In view of the analytical bottleneck of the autoregressive paradigm, it introduces a debate mechanism to try to avoid factual illusion through heterogeneous falsification paths [3, 6, 8]. The effectiveness of such systems depends largely on the heterogeneous nature of their internal roles. Especially in dealing with complex tasks, the architecture optimized by role decoupling not only significantly improves the consistency index, but also ensures the substantial improvement of analytical accuracy [12]. Its core is to break the compliance tendency of the model to blindly cater to the context by constructing the objective

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function of mutual confrontation. This transformation promotes the evolution of semantic parsing to the dimension of evidence-based game theory, and provides the possibility of logical reduction in IA [6, 8]. Under this new paradigm, the system is no longer just an auxiliary tool, but an independent subject with the ability to critically examine.

The introduction of a logical recovery mechanism essentially defines the evolution boundary of the transition from simple task collaboration to a dynamic audit paradigm [13]. Under this new paradigm, the system is no longer just an auxiliary tool, but an independent subject with the ability to critically examine. Most of the existing studies are limited to the collaborative topology, focusing on the synthesis of financial summaries or the emotional stripping of the surface, ignoring the conflict of economic interests. Due to the lack of constraints on the game between execution units, these models often lack the necessary awareness of prevention and hedging means in the face of tone manipulation [7, 11]. It can be seen that the essence of the introduction of the confrontation mechanism is to establish a rigorous set of technical audit mapping for the defense logic of M&a pricing [4]. This fundamental transformation from linear reasoning to adversarial topology has laid a solid foundation for the construction of a self-consistent asset valuation framework [4].

2.3. Acquisition scenario adaptation bottleneck

Although the adversarial structure has provided preliminary support for asset valuation, the research on interactive protocols and cross-modal paths lags in the context of M&A [13]. At the underlying protocol level, the existing framework is difficult to restore the mechanism of cross-examination based on the evidence chain [4]. In the absence of opposing objective functions and audit nodes, once such structures encounter tone manipulation or financial embellishment, it is easy to blindly trust and trigger the risk of logical endorsement [6, 12]. In addition, from the perspective of evaluation dimension, the application of existing game theory is often limited to the price scalar dimension, and due to excessive dependence on coarse-grained indicators, the reasoning chain seriously lacks the necessary falsification mechanism and objective logic constraints in the face of complex games [2, 8, 12]. At the level of cross-modal mapping, most of the mainstream models are static extraction. Due to the lack of a feedback regulation mechanism, it can not support the dynamic interaction between semantic logic and valuation algorithms, and it is difficult to transform unstructured features into quantitative parameters [14-16]. This will make the transformation process lack the rigorous support, which will weaken the credibility of the overall model [9, 13].

In view of this mismatch, this study reconstructs the mapping framework to realize seamless connection between semantic insight and dynamic parameter adjustment. With interactive protocols and cross-model paths, the framework not only bridges the application gap, but establishes a new theoretical paradigm for FV anchoring assets in complex trading environments [1, 4].

3. Merger and acquisition pricing cross-questioning framework

3.1. Heterogeneous roles and cognitive modeling

Under this paradigm, the core of achieving closed-loop mapping lies in deconstructing the pricing task into heterogeneous functional units with opposing constraints [13, 17]. By simulating game theory in an asymmetric environment, the deep decoupling of functional roles helps to enhance the objectivity of pricing outcomes [6, 12]. Figure 1 illustrates the theoretical framework of cross-examination, which integrates data foundation, camp collaboration, and controlled game from the

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bottom up. It aims to clarify how the mapping between cognitive traits and functional boundaries drives the leap from static assessment to dynamic game in M&A pricing [13, 17].

The evolution of dynamic games essentially depends on the deep coupling between heterogeneous cognitive traits and the constraints of conflict of interest [4]. Table 1 reveals the real motivations behind M&A pricing by deconstructing the seller, buyer, and audit teams [12]. An initial claim with a biased expectation forms the starting point of the game, forcing the opposing camp to perform evidence-driven information calibration and effectively stripping away irrational premiums [6, 8]. In response to negotiation deadlocks caused by extreme disagreements, an independent auditing entity is dedicated to monitoring interactions and extracting consensus in order to achieve the ultimate goal of objective asset valuation [1, 12, 18].

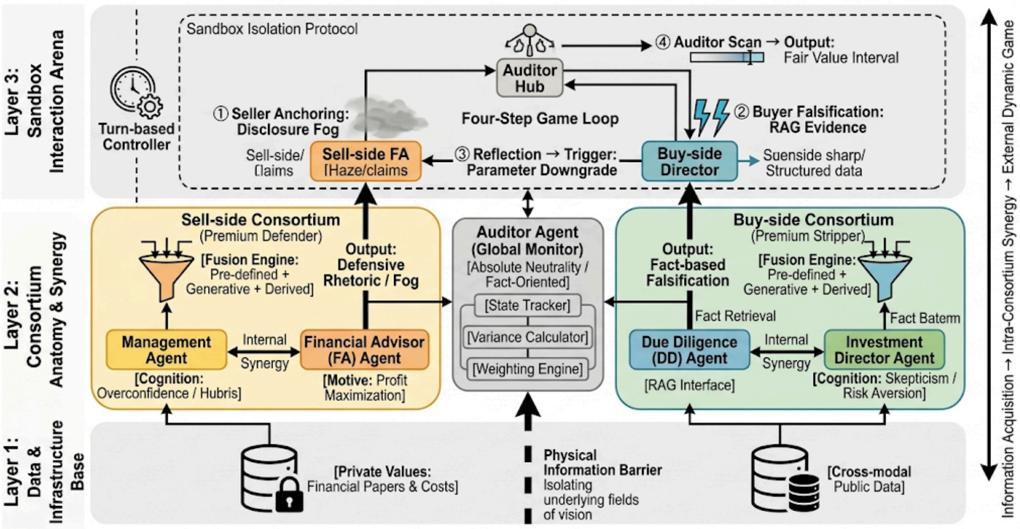

Figure 1. Multi-agent cross-questioning architecture for M&A pricing: integration camp collaboration and controlled game mechanism (picture credit: original)

Table 1. Mapping of cognitive traits and functional boundaries among multi-agents

Game factions	Reality mapping	Cognitive traits	Decision constraints	Game objective	Literature
seller	Target executives, financial advisors	Overconfidence, arrogance	Maximize valuation	Construct valuation anchors, defensive rhetoric	[2, 3, 15]
buyer	Institutional investors, due diligence team	Skepticism, risk aversion	Logical falsification	Dispel the fog of disclosure, strip away the premium	[5, 6, 19]
auditor	Independent directors, external auditors	Neutral, objective	Consensus Extraction	Monitor deductive logic, guide value convergence	[7, 18]

3.2. Challenge protocol and topology design

In order to make the dynamic game environment rigorous, the system architecture must accurately map the characteristics of information asymmetry in M&A practice [17]. At the topology level, the existing literature uses the isolation mechanism to build an information barrier and blocks unauthorized access to private logic by means of authority differentiation and one-way shielding.

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This mechanism not only defends the underlying logic of asymmetric games, but also significantly suppresses the risk of information spillover [12, 17].

In the interactive dimension, relying on the established topological constraints, factional competition at the interactive level is instead driven by structured protocols [19]. The agreement aims to standardize valuation claims to eliminate semantic ambiguity, so as to ensure accurate docking between deterministic judgments and quantitative parameters [5, 11]. In order to correct the reasoning bias of LLMS in the financial field, the paradigm establishes a dynamic verification logic, that is, to correct its reasoning path in real time according to the deviation of semantic parameters from the underlying benchmark [5, 11].

In the time dimension, the system embeds the round control mechanism into the sequential game framework [12]. Through dynamic multi-round debate and sequence convergence technology, the original discrete interaction can be integrated into strong logical reasoning. This not only avoids the trap of logical recurrence but also greatly improves the convergence rate of the game [7, 8]. The synergy of isolation mechanism, structured agreement, and round control jointly solves the game problems caused by IA in M&a practice, thus providing a rigorous deduction logic for determining the FV of assets [4, 6].

3.3. Dynamic logic and parameter correction

Relying on the construction of protocol and topology constraints, the system can map the preset heterogeneous function to the dynamic interaction in the pricing game. The game takes the seller's quotation as the starting point, and deeply integrates the buyer's logical falsification behavior with the auditor's neutral supervision function. Driven by profit incentives, sellers tend to construct optimistic, biased growth narratives and valuation commitments [3].In view of the above tendencies, the buyer transforms the original static text audit into a dynamic game model through the empirical comparison of objective financial data [6]. Under strict inquiry guidelines, if the seller's reply fails to provide factual support, the verification mechanism will automatically determine that it is invalid [8]. The game-based evidence chain forces the reasoning of both sides to converge to objective fundamentals, guides the seller to make valuation concessions, and then is transformed into instructions driving the iteration of the valuation model [1, 8, 14]. Table 2 further clarifies the specific quantitative mechanism for the transformation of semantic risk characteristics into valuation parameters. Once the narrative defect is detected, the system will prompt the evaluation subject to compile a supporting adjustment plan. Once the fault between qualitative evidence and quantitative data is detected, the original preset correction instructions will be rejected by the architecture [6, 8].

Table 2. Quantitative mapping mechanism between semantic risk features and valuation parameters

Semantic challenge feedback	Financial Logic Mapping	Valuation parameter adjustment action	Literature
Lack of evidence of growth	Optimistic bias, prediction distortion	Lower revenue growth forecast, deduct free cash flow	[2, 5]
Textual logical contradictions	Adverse selection, loss of transparency	Increase discount rate, raise risk premium	[11, 14]
unusually positive tone	Agency conflict, overconfidence	Increase capital costs, accrue agency discounts	[3, 14, 20]
Cooperative path fuzzy	Integrating risk, asset specialization	Reduce the terminal value of the synergy, accrue restructure costs	[2, 6]

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Table 2. (continued)

Strategic greenwashing suspicion	Compliance defects, reputational damage	Accrue contingencies, Trim terminal growth	[15, 19]

In view of the operation and verification needs of valuation logic, the system introduces independent audit subjects to track the whole process of the game in real time and evaluate the evidence effectiveness of the evidence chain [7]. It provides a clear definition of the FV range of the underlying assets by extracting the key dimensions in the consensus parameters [1, 18]. This link has effectively curbed the common compliance deviations of LLMS and ensured that the parameter adjustment always follows the financial logic [6, 12]. With the cooperation of third-party supervision and a consensus extraction mechanism, the cross-questioning system finally guides the dynamic game process to converge to FV [8].

4. Constraints and evolution trends

Although previous literature has initially demonstrated the theoretical framework of moving from semantic game to numerical convergence, its landing is still subject to multiple constraints in the process of migrating to complex real scenarios [9, 10, 13]. To drive the system towards a dynamic empirical environment, must give priority to cracking the following three key bottlenecks:

First, it is about the interpretability of reasoning logic and its internal causal attribution. Limited by the black box effect of the model, the deduction path of the valuation parameters of inquiry output is opaque, which hinders the construction of trust with the audit system [9, 10]. Future research should strengthen the integration of evidence retrieval and investigation to ensure that quantitative parameters are always anchored to publicly disclosed text benchmarks [11]. Only by establishing a pricing traceability mechanism with structural characteristics can fundamentally resolve the issue of transparency [8].

Second, it involves the game dilemma between data island and privacy protection in a collaborative environment. M&A pricing is highly dependent on non-public private ownership documents, and the existing mechanism is limited by public texts and difficult to obtain core secrets [9, 10].In the future, privacy protection protocols need to be embedded at the bottom to facilitate the collaboration of agents in a physically isolated environment [10, 12]. By making the raw data available and invisible, a solid compliance boundary is built for the dynamic game involving trade secrets while extracting [10].

Thirdly, it focuses on the integration of regulatory compliance and the challenge of building an algorithmic audit system. M&A pricing is strictly regulated, and current models often underestimate the semantically induced emotional contagion effect and its potential tail risk [3, 4]. This blind spot of verification based on game theory constitutes an institutional obstacle to practical implementation. The future direction is to develop an audit system adapted to financial standards and use stress testing to provide real-time insight into valuation robustness, so as to drive the iteration of pricing paradigm in a changing empirical environment [1, 10].

5. Conclusion

To address the valuation distortions caused by IA and management rhetoric manipulation in M&A pricing, this study systematically traces the evolution of technology and constructs a structured pricing paradigm based on multi-agent cross-interrogation. This mechanism breaks through the limitations of static analysis in single large models and innovatively realizes cross-modal mapping

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from unstructured semantic adversarial to structured estimation parameter correction. Through game-theoretic decoupling among heterogeneous camps and independent audit monitoring, the system constructs rigorous endogenous constraints, effectively strips away irrational premiums, and drives asset valuations to converge toward objective FV. However, given the data silos and compliance barriers that are prevalent in real capital markets, the future evolution of the architecture urgently needs to promote the deep integration of privacy computing and penetrating algorithm auditing. This dynamic inquiry paradigm will ultimately reshape the asset valuation benchmark under human-machine collaboration, establishing a robust safety boundary for complex financial decisions.

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