

A Hybrid Mathematical–Economic and Artificial Intelligence Framework for Competitive Market Analysis and Strategic Positioning

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1. Introduction and problem statement

Competitive analysis is a crucial component for firms and regulators operating in dynamic and rapidly evolving markets. A clear understanding of market structure and competition intensity enables informed strategic decisions, risk anticipation, and improved positioning. Markets characterized by substitutable or overlapping products, complex interactions between firms, and structural volatility demand analytical frameworks that go beyond static economic indicators or isolated machine learning techniques.

Traditional mathematical–economic models provide well-established tools for assessing market power and concentration, yet they often fall short in capturing short-term and complex dynamics, non-stationarity, and anticipatory behavior. Furthermore, artificial intelligence (AI) methods excel at pattern recognition and forecasting but may lack theoretical economic grounding. Regulatory bodies, like firms, must monitor markets in real time to adapt regulations and ensure fair competition as market conditions evolve.

In this research paper, we propose a hybrid framework that combines mathematical–economic modeling with AI-based methods to assist both regulators and firms in analyzing competitive markets. The goal is to develop a decision-support and early-warning system capable of evaluating competition intensity, ranking market participants, forecasting short-term competitive dynamics, and anticipating the entry of new competitors.

2. Hybrid modeling framework

The proposed framework is designed to serve both firms aiming to remain competitive and regulators seeking to monitor and intervene in market dynamics. We consider a market consisting of multiple firms offering substitutable or partially overlapping products or services.

To address the complexity of market analysis, the framework adopts a modular architecture, organized into four interconnected stages. Each stage focuses on a specific analytical task— from structural competition modeling to behavioral forecasting—and feeds into the next step, ensuring both specialization and continuity across the process. The hybrid framework is structured into four sequential stages:

- **Economic Competition Modeling:**

We have employed four widely used indicators to quantify structural and behavioral competition: the Herfindahl–Hirschman Index (HHI) [1, 2] is used for market concentration, the Lerner Index [3] for measuring market power, the Boone Indicator [4–6] for assessing efficiency-related competition, and the Panzar–Rosse H-statistic [7] for evaluating

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market conduct. These indicators, grounded in mathematical–economic theory, provide interpretable and analytically rigorous insights into market structure and dynamics.

- **Clustering and Positioning:**

All the firms in the market are clustered and ranked using unsupervised machine learning techniques, enabling the identification of strategic groups and the assessment of relative positioning among them. Algorithms such as k-means, hierarchical clustering, and density-based spatial clustering of applications with noise (DBSCAN) [8] are used to group firms into meaningful categories such as leaders, challengers, and new entrants, based on multi-dimensional performance indicators.

- **Forecasting Market Dynamics:**

We have applied time-series forecasting models and deep learning architectures to predict the evolution of competition intensity. Recurrent neural networks (RNNs) [9], including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), along with statistical models, are used to capture temporal dependencies and nonlinearities in market behavior.

- **Simulation and Anticipation via AI:**

In the final component, we integrate generative adversarial networks (GANs) and multi-agent reinforcement learning (MARL) to simulate potential market scenarios and anticipate the behavior of new entrants and strategic responses of existing actors [10–13]. These AI components support proactive rather than reactive decision-making.

This integrated framework is designed to be adaptable across various sectors—including insurance, banking, and other competitive industries—and offers a ready-to-use tool for researchers, strategists, and regulators. All AI models have been fine-tuned to be applied in the context of competitive market analysis.

3. Preliminary Results and Discussion

At this stage, the model remains at a conceptual and architectural level. We have conducted preliminary simulations using synthetic market data to test how well the different components work together. The results indicate that combining economic competition indicators with AI techniques — including clustering, forecasting, GAN-based scenario generation, and multi-agent simulations — leads to clearer interpretations and better predictive outcomes than relying on a single type of model. These early findings support the relevance and potential of our hybrid framework for understanding competitive markets.

4. Conclusion and Perspectives

In this research, we have introduced a hybrid, modular, and extensible framework that bridges the rigor of economic theory with the adaptability and scalability of artificial intelligence. It addresses the need for real-time, interpretable, and proactive market analysis tools suited to highly dynamic and competitive environments.

Ongoing and future work focuses on empirical validation using real-world market datasets, refining the interoperability between AI models and economic constraints, and extending the framework for broader applications, including policy evaluation and strategic simulation for regulatory and enterprise-level decision-making.

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References

- [1] O. Herfindahl. “Concentration in the U.S. Steel Industry”. Ph.D. dissertation. Columbia University, 1950.
- [2] A. O. Hirschman. *National Power and the Structure of Foreign Trade*. 1st. Berkeley: University of California Press, 2018.
- [3] A. P. Lerner. “The Concept of Monopoly and the Measurement of Monopoly Power”. In: *The Review of Economic Studies* 1.3 (1934), pp. 157–175. DOI: [10.2307/2967480](https://doi.org/10.2307/2967480).
- [4] J. Boone. “Intensity of Competition and the Incentive to Innovate”. In: *International Journal of Industrial Organization* 19.5 (2001), pp. 705–726. DOI: [10.1016/S0167-7187\(00\)00090-4](https://doi.org/10.1016/S0167-7187(00)00090-4).
- [5] J. Boone. *A New Way to Measure Competition*. Discussion Paper 2004-004. TILEC, 2004.
- [6] J. Boone. “A New Way to Measure Competition”. In: *The Economic Journal* 118.531 (2008), pp. 1245–1261. DOI: [10.1111/j.1468-0297.2008.02168.x](https://doi.org/10.1111/j.1468-0297.2008.02168.x).
- [7] J. C. Panzar and J. N. Rosse. “Testing For “Monopoly” Equilibrium”. In: *The Journal of Industrial Economics* 35.4 (1987), p. 443. DOI: [10.2307/2098582](https://doi.org/10.2307/2098582).
- [8] G. Tang, R. Tian, and B. Wu. “An Overview of Clustering Methods in The Financial World”. In: *Proceedings of the International Conference*. Zhuhai, China, 2022. DOI: [10.2991/aebmr.k.220307.084](https://doi.org/10.2991/aebmr.k.220307.084).
- [9] I. D. Mienye, T. G. Swart, and G. Obaido. “Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications”. In: *Information* 15.9 (2024), p. 517. DOI: [10.3390/info15090517](https://doi.org/10.3390/info15090517).
- [10] D. Wilson and A. Azmani. “Generative Adversarial Networks: A Systematic Review of Characteristics, Applications, and Challenges in Financial Data Generation and Market Modeling: 2019–2024”. In: *International Journal of Engineering* 39.2 (2026), pp. 395–406. DOI: [10.5829/ije.2026.39.02b.09](https://doi.org/10.5829/ije.2026.39.02b.09).
- [11] L. Xu, M. Skoularidou, A. Cuesta-Infante, and K. Veeramachaneni. *Modeling Tabular Data Using Conditional GAN*. 2019. DOI: [10.48550/ARXIV.1907.00503](https://doi.org/10.48550/ARXIV.1907.00503). arXiv: [arXiv:1907.00503 \[cs.LG\]](https://arxiv.org/abs/1907.00503).
- [12] H. Xia, S. Sun, X. Wang, and B. An. “Market-GAN: Adding Control to Financial Market Data Generation with Semantic Context”. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 38. 14. 2024, pp. 15996–16004. DOI: [10.1609/aaai.v38i14.29531](https://doi.org/10.1609/aaai.v38i14.29531).
- [13] J. Liang, H. Miao, K. Li, J. Tan, X. Wang, R. Luo, and Y. Jiang. “A Review of Multi-Agent Reinforcement Learning Algorithms”. In: *Electronics* 14.4 (2025), p. 820. DOI: [10.3390/electronics14040820](https://doi.org/10.3390/electronics14040820).