Technical Execution Plan: Learning Hierarchical Influence Propagation in Organizational Response Systems

Hilal Hussain, Mahmoud Abdelmoneum, Theo Chen

October 29, 2025

I. Problem Statement

Organizations regularly receive external recommendations—from consultants, regulatory bodies, boards of directors, or internal initiatives—yet their response patterns remain difficult to predict. The challenge lies in understanding how these recommendations propagate through complex organizational hierarchies, where individual agents possess varying degrees of power and influence, operate under partial information, and engage in strategic interactions that affect collective outcomes. Existing organizational behavior models either treat organizations as monolithic entities or fail to capture the dynamic interplay between individual decision-making and collective organizational response (Hansen & Pigozzi, 2024; Li et al., 2025).

Traditional approaches to modeling organizational decision-making suffer from three fundamental limitations. First, they typically rely on static network models that do not account for the temporal dynamics of influence propagation (Valente, 2006). Second, they fail to model the strategic nature of agent interactions within hierarchies, where individuals optimize their responses based on anticipated actions of others and organizational power structures. Third, existing methods cannot effectively leverage textual descriptions of organizations and recommendations to generate predictions, limiting their applicability to real-world scenarios where structured data is scarce but qualitative descriptions are abundant.

Our project addresses these limitations by formulating organizational response prediction as a hierarchical partially observable stochastic game (H-POSG), where agents at different organizational levels make sequential decisions under uncertainty while influencing one another through a dynamic authority graph. The core research question is: *Can deep learning models learn effective representations of organizational dynamics from text descriptions to predict both individual agent responses and collective organizational outcomes, while respecting the game-theoretic properties of hierarchical strategic interaction?*

II. Proposed Solution

We propose a novel framework that integrates game-theoretic formalization with deep learning architectures to model and predict organizational response dynamics. Our approach consists of three interconnected components that map qualitative text inputs to structured predictions over agent responses and organizational adoption outcomes.

Theoretical Framework

We formalize the organizational response system as a Hierarchical Partially Observable Stochastic Game defined by the tuple $\langle \mathcal{I}, \mathcal{S}, \{\mathcal{A}_i\}, \{\mathcal{O}_i\}, P, \Omega, \{R_i\}, G \rangle$ where: $\mathcal{I} = \{1, \ldots, n\}$ represents the set of agents (organizational members); $\mathcal{S}$ is the organizational state space encoding agent beliefs, relationships, and context; $\mathcal{A}_i$ is agent i's action space representing possible responses to recommendations; $\mathcal{O}_i$ is agent i's observation space (partial view of organizational state); $P : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$ is the state transition function capturing how individual actions propagate through the organization; $\Omega : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{O})$ is the observation function; $R_i : \mathcal{S} \times \mathcal{A} \times \mathcal{S}' \to \mathbb{R}$ is agent i's reward function reflecting individual objectives; and $G = (\mathcal{I}, E, W)$ is the authority graph with edge weights $w_{ij} \in \mathbb{R}^+$ representing influence strength from agent j to agent i (Li et al., 2025; Emery-Montemerlo et al., 2004).

Each agent i operates at hierarchy level $\ell(i) \in \{1, \ldots, k\}$ with power level $\rho_i \in [0, 1]$, where higher values indicate greater organizational authority. Agent policies are hierarchical: $\pi_i(o_i, h_i) \to \Delta(\mathcal{A}_i)$, where h_i represents the history of higher-level agent actions that constrain lower-level decisions (Zhang et al., 2024).

Deep Learning Architecture

Our architecture combines dual encoders for text-to-representation learning with graph neural networks for influence propagation modeling.

Text Encoding Layer: We employ two transformer-based encoders (Vaswani et al., 2017): a recommendation encoder $f_r : \mathcal{T}_r \to \mathbb{R}^d$ that maps textual recommendation descriptions to a d-dimensional embedding space, and an organizational context encoder $f_c : \mathcal{T}_c \to \mathbb{R}^d$ that encodes organizational structure, culture, and historical response patterns. These encoders utilize pre-trained language models fine-tuned on organizational text data.

Graph Propagation Layer: Given the authority graph G and encoded representations, we employ a graph attention network to model influence propagation (Yang et al., 2021). For agent i at time t, the aggregated influence from neighbors is computed as

$$\mathbf{m}_i^{(t)} = \text{AGG}\left(\left\{\alpha_{ij}^{(t)} \mathbf{h}_j^{(t-1)} : j \in \mathcal{N}(i)\right\}\right),$$

where $\mathbf{h}_j^{(t-1)}$ is agent j's hidden state at time $t-1$, $\alpha_{ij}^{(t)}$ are learned attention weights reflecting influence strength, and $\mathcal{N}(i)$ denotes agent i's neighbors in the authority graph.

Hierarchical Policy Network: Each agent's response distribution is predicted by a policy network that takes as input the recommendation embedding, organizational context embedding, agent-specific features (power level, role), and aggregated neighbor influences:

$$\pi_i(a_i|o_i, \mathbf{m}_i, f_r, f_c) = \text{softmax}\left(W_{\text{out}} \cdot \text{MLP}\left([\mathbf{h}_i, f_r, f_c, \mathbf{m}_i]\right)\right),$$

where $[\cdot]$ denotes concatenation and MLP is a multi-layer perceptron with hierarchical conditioning (Chen et al., 2023).

Learning Objective

We train the model using a multi-objective loss function that combines supervised prediction loss with game-theoretic regularization:

$$\mathcal{L} = \mathcal{L}_{\text{pred}} + \lambda_1 \mathcal{L}_{\text{consistency}} + \lambda_2 \mathcal{L}_{\text{equilibrium}},$$

where $\mathcal{L}_{\text{pred}}$ is the cross-entropy loss for predicting individual agent actions and collective outcomes; $\mathcal{L}_{\text{consistency}}$ enforces temporal consistency in agent behavior across similar scenarios; and $\mathcal{L}_{\text{equilibrium}}$ encourages learned policies to satisfy hierarchical Nash equilibrium conditions (Jiang & Lu, 2021). The model is trained using multi-agent policy gradient methods adapted for hierarchical games (Chen et al., 2025).

III. Literature Review

Multi-Agent RL and Stochastic Games. Stochastic games extend MDPs to multi-agent settings where agents' actions jointly determine state transitions and individual rewards (Smith & Jones, 2025). POSG research develops solution concepts and algorithms for settings with incomplete information (Hansen et al., 2004). Temporal-difference learning forms a core algorithmic tool in MARL (Barfuss, 2021) with finite-time analyses in the multi-agent setting (Dal Fabbro et al., 2024), while policy gradient and actor-critic methods provide effective learning in partially observable, continuous settings (Wen et al., 2021).

Hierarchical Multi-Agent Systems. Hierarchical organization is captured via design patterns such as leader–follower and layered decision-making, mapping naturally to Stackelberg formulations (Li et al., 2025; Jiang & Lu, 2021). Agent-based organizational models provide rule-based simulations to study emergent phenomena and information flow (Harrington, 2012; Hansen & Pigozzi, 2024). HRL advances inform multi-level policy design and option discovery for structured control (Zhang et al., 2024).

GNNs for Social Influence. GNNs model diffusion and influence dynamics via neighborhood aggregation and attention, enabling accurate prediction of cascade behavior and node-level influence (Yang et al., 2021; Li et al., 2024). Attention-weight analysis connects learned edges to influence strength and centrality in social and organizational graphs (Zhang et al., 2024).

Dual Encoders and Text Embeddings. Dual encoders project heterogeneous text inputs (e.g., recommendations vs. organizational context) into a shared space for compatibility and response prediction (Emergent Mind, 2025; DeepLearning.AI, 2024). Contrastive learning improves alignment of semantically related pairs and robustness (Liu et al., 2025).

Synthetic Data Generation. LLMs enable high-fidelity synthetic datasets where real data are scarce, with methods for prompt design, constraints, and privacy (Confident AI, 2025; Chen et al., 2025; Google Research, 2025).

IV. Technical Execution Details of Proposed Solution $\rightarrow$ Dataset + Modeling

Dataset Construction

Synthetic Dataset Generation Pipeline. We will construct a comprehensive synthetic dataset in three stages. Stage 1 generates diverse organizational structures (size, hierarchy depth, span of control, culture, industry) and corresponding authority graphs with influence weights. Stage 2 synthesizes recommendations across strategic, operational, policy, and crisis domains annotated with urgency, resources, risk, and culture alignment. Stage 3 simulates multi-step response trajectories for each agent at times $t \in \{0, 1, 2, 3\}$ capturing initial reactions, peer effects, leader input, and final decisions. We target 10,000 organizations, 75 recommendations each, producing 750k agent-level responses split 70/15/15.

Real-World Data Collection. We will curate 500–1000 cases from business schools' repositories, organizational behavior literature, corporate reports, regulatory filings, and news, extracting organizational context, recommendations, and documented responses for validation and fine-tuning.

Agent-Based Simulation Baseline. A rule-based ABM will simulate agent heuristics (risk tolerance, departmental alignment, status influence, coalition dynamics, norms), generating 100k scenarios to benchmark and augment training data (Harrington, 2012).

Model Architecture and Implementation

Text Encoders. Two transformer encoders (BERT/RoBERTa-large) produce 768-d embeddings for recommendations and organizational contexts, jointly fine-tuned with contrastive loss for alignment (Vaswani et al., 2017; DeepLearning.AI, 2024).

Graph Neural Network. A 4-layer multi-head GAT (8 heads) aggregates influence over the authority graph with residual connections and ELU activations, unrolled for $T = 3$ steps to capture temporal propagation (Yang et al., 2021).

Hierarchical Policy Network. An MLP ingests concatenated vectors [agent hidden state, recommendation embedding, context embedding, aggregated neighbor influence] to predict a 5-class response distribution via softmax, with explicit conditioning on higher-level agents' predictions.

Training Objective and Optimization. The loss $\mathcal{L} = \mathcal{L}_{\text{pred}} + 0.1\mathcal{L}_{\text{consistency}} + 0.05\mathcal{L}_{\text{equilibrium}}$ combines cross-entropy, temporal consistency, and equilibrium regularization. Optimization uses

AdamW (1e-4 LR, warmup 5k steps, cosine decay), batch size 32 organizations, gradient clipping 1.0, early stopping on validation loss.

Stack and Resources. PyTorch 2.x, PyTorch Geometric, Hugging Face Transformers; 4x A100 GPUs with mixed precision; estimated 48 hours for full training.

V. Detailed Technical Roadmap/Timeline To Achieve Proposed Solution, Including 4 Week Plan

Weeks 1–2: Infrastructure and Baselines. Week 1: environment setup, data structures, DataLoader utilities, bag-of-words + logistic regression baseline (target 40–50% on simple synthetic). Week 2: implement LLM-based generation for organizational structures, generate 1k organizations, implement rule-based ABM, and data validation utilities with deliverable of 50k agent responses and documentation.

Weeks 3–4: Core Model Development. Week 3: implement dual encoders with contrastive training, basic 2-layer GAT, and integrate for initial runs (target 55–60%). Week 4: extend GNN to 4 layers with temporal modeling, add hierarchical conditioning, integrate full pipeline, and conduct hyperparameter search (target 65–70%).

First Project Break: Hypotheses and Experimental Design. Analyze early results and define hypotheses: H1 hierarchical cascades; H2 centralization accelerates consensus; H3 culture-aligned recommendations garner uniform support; H4 power moderates peer influence. Design controlled experiments, expand dataset to 5k organizations (350k responses), and finalize evaluation protocol.

Weeks 5–6: Scaled Training and Initial Experiments. Week 5: train full model on expanded data, implement exploitability and stability metrics, run ablations (remove GNN/hierarchy/contrastive), visualize attention patterns. Week 6: test H1 and H2 with correlation analyses and centrality metrics, begin real-world data collection.

Weeks 7–8: Advanced Experiments and Validation. Week 7: test H3 (culture alignment) and H4 (power moderation), run cross-domain generalization (industries, sizes, cultures), fine-tune on real cases. Week 8: validate against real cases, analyze equilibrium approximation, sensitivity tests, and compare to MARL baselines.

Second Project Break: Refinement and Analysis. Identify best architectural variants (optimal GNN depth, hierarchical attention), implement improvements (temporal transformers, multi-scale GNNs), conduct comprehensive ablations, analyze failure modes, draft theoretical analysis, and generate final 10k-organization dataset (750k responses).

Weeks 9–10: Finalization. Week 9: train final model, complete evaluation (accuracy, equilibrium, generalization, real-world validation), implement interpretability (SHAP, counterfactuals), and produce visualizations. Week 10: synthesize results, write report, prepare presentation, package code and weights, and perform quality checks.

Four-Week Detailed Plan (Weeks 1–4). Week 1: Days 1–2 infra; Days 3–4 graph data schemas;

Days 5–6 DataLoader; Day 7 baseline. Week 2: Days 1–2 prompts; Days 3–4 generate 1k orgs; Days 5–6 ABM; Day 7 data QA. Week 3: Days 1–2 encoders; Days 3–4 contrastive training; Days 5–6 GAT; Day 7 integration tests. Week 4: Days 1–2 temporal GNN; Days 3–4 hierarchical policy; Days 5–6 pipeline; Day 7 hyperparameter search.

VI. Evaluation Methods

Predictive Accuracy. Individual response prediction via accuracy, macro F1, top-2 accuracy, and per-level accuracy; organizational outcome prediction via adoption accuracy, consensus time MAE, and support distribution KL divergence.

Equilibrium Properties. Nash approximation via exploitability and best-response deviation; hierarchical consistency via Stackelberg constraint violations and a rationality score (Jiang & Lu, 2021).

Influence Propagation Fidelity. Attention–influence correlation and centrality alignment; causal precision/recall on synthetic ground-truth cascades (Yang et al., 2021; Li et al., 2024).

Generalization and Robustness. Cross-industry/size/culture generalization, real-case validation with expert review, and adversarial robustness to text, graph, and feature perturbations.

Ablations and Interpretability. Architectural, objective, and data ablations; attention visualization over org charts; SHAP feature importance and counterfactuals for sensitivity analysis.

VII. References

[1] Barfuss, W. (2021). Dynamical systems as a level of cognitive analysis of multi-agent learning. *Nature Communications*, 13. https://pmc.ncbi.nlm.nih.gov/articles/PMC8827307/

[2] Chen, X. et al. (2023). Hierarchical Graph Neural Networks for Causal Discovery and Root Cause Analysis. *arXiv*. https://arxiv.org/abs/2302.01987

[3] Chen, Y. et al. (2025). Learning Individual Behavior in Agent-Based Models with Graph Neural Networks. *arXiv*. https://arxiv.org/html/2505.21426v1

[4] Chen, Z. et al. (2025). Synthetic Data Generation Using Large Language Models. *arXiv*. https://arxiv.org/abs/2503.14023

[5] Chen, K. et al. (2025). K-Level Policy Gradients for Multi-Agent Reinforcement Learning. *arXiv*. https://arxiv.org/abs/2509.12117

[6] Confident AI. (2025). Using LLMs for Synthetic Data Generation: The Definitive Guide. https://www.confident-ai.com/blog/the-definitive-guide-to-synthetic-data-generation-using-llms

[7] Dal Fabbro, N. et al. (2024). Finite-Time Analysis of Asynchronous Multi-Agent TD Learning. *arXiv*. https://arxiv.org/abs/2407.20441

[8] DeepLearning.AI. (2024). Embedding Models: From Architecture to Implementation. https://learn.deeplearnin models-from-architecture-to-implementation/lesson/vu3si/introduction

[9] Emergent Mind. (2025). Dual Encoder Architecture. https://www.emergentmind.com/topics/dual-encoder-architecture

[10] Emery-Montemerlo, R. et al. (2004). Dynamic Programming for Partially Observable Stochastic Games. *AAAI*. http://www.ccs.neu.edu/home/camato/publications/aaai-SS-04.pdf

[11] Google Research. (2025). Generating Synthetic Data with Differentially Private LLM Inference. https://research.google/blog/generating-synthetic-data-with-differentially-private-llm-inference/

[12] Hansen, E. et al. (2004). Dynamic Programming for Partially Observable Stochastic Games. *AAAI*. http://www.ccs.neu.edu/home/camato/publications/aaai-SS-04.pdf

[13] Hansen, A. & Pigozzi, G. (2024). An Agent-Based Model of Hierarchical Information-Sharing in Organizations. *JASSS*, 27(2). https://www.jasss.org/27/2/2.html

[14] Harrington, J. (2012). Agent-Based Models of Organizations. *Handbook of Computational Economics*. https://joeharrington5201922.github.io/pdf/HCE-12.05.pdf

[15] Jiang, A. & Lu, Z. (2021). Equilibrium Refinements for Multi-Agent Influence Diagrams. *arXiv*. https://arxiv.org/abs/2102.05008

[16] Li, S. et al. (2024). Maximizing Influence with Graph Neural Networks. *ACM WSDM*. https://dl.acm.org/doi/10.1145/3625007.3627293

[17] Li, Y. et al. (2025). A Taxonomy of Hierarchical Multi-Agent Systems: Design Patterns and Architectures. *arXiv*. https://arxiv.org/abs/2508.12683

[18] Liu, M. et al. (2025). A Dual-Encoder Contrastive Learning Model for Knowledge Tracing. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC12294018/

[19] Smith, R. & Jones, T. (2025). Unilateral Incentive Alignment in Two-Agent Stochastic Games. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC12207489/

[20] Valente, T. (2006). Interorganizational Network Structures and Diffusion of Information Through Organizations. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC1963276/

[21] Vaswani, A. et al. (2017). Attention Is All You Need. *NeurIPS*. https://arxiv.org/abs/1706.03762

[22] Wen, M. et al. (2021). Characterizing the Gap Between Actor-Critic and Policy Gradient. *ICML*. https://proceedings.mlr.press/v139/wen21b/wen21b.pdf

[23] Yang, Y. et al. (2018). Mean Field Multi-Agent Reinforcement Learning. *ICML*. https://proceedings.mlr.press/

[24] Yang, H. et al. (2021). Enhance Information Propagation for Graph Neural Networks. *arXiv*. https://arxiv.org/abs/2102.04064

[25] Zhang, J. et al. (2024). Bidirectional-Reachable Hierarchical Reinforcement Learning with Mutually Accessible Options Discovery. *arXiv*. https://arxiv.org/abs/2406.18053

[26] Zhang, L. et al. (2024). The Influence Maximization Algorithm for Integrating Attribute Graph and Social Network. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC11550086/