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Deep Neural Network-Based Coupling Model of Inter-Organizational Knowledge Flow and Agent Collaborative Decision-Making

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ABSTRACT

Inter-organizational knowledge flow and agent collaborative decision-making constitute mutually interdependent processes critical for organizational performance in complex environments. This study proposes a novel deep neural network-based framework that explicitly models the bidirectional coupling mechanism between knowledge propagation dynamics and multi-agent coordination. The architecture integrates graph attention networks for knowledge transfer modeling with multi-agent reinforcement learning for decision coordination, establishing coupling interfaces that enable dynamic adaptation between these subsystems. The model incorporates temporal decay mechanisms, attention-based knowledge path optimization, and closed-loop feedback that propagates decision outcomes back to reshape knowledge transfer patterns. Experimental validation on synthetic and real-world datasets demonstrates substantial performance improvements of 8-24% over state-of-the-art baselines across knowledge transfer accuracy, decision success rates, and coordination efficiency metrics. Deployment in a supply chain coordination scenario achieved 18.5% cost reduction, 71% stockout frequency decrease, and 42.7% inventory turnover improvement. The coupling quality correlation coefficient reached 0.812, confirming strong interdependencies between knowledge evolution and decision outcomes. This work advances theoretical understanding of organizational knowledge systems while providing practical tools for enhancing inter-organizational collaboration.

KEYWORDS

Inter-organizational knowledge flow; Agent collaborative decision-making; Deep neural networks; Coupling mechanism; Graph neural networks; Multi-agent systems

I. Introduction

In the era of digital economy, inter-organizational knowledge flow has emerged as a critical driver of innovation and competitive advantage, fundamentally reshaping how organizations create, transfer, and utilize knowledge across boundaries [1]. The rapid advancement of artificial intelligence technologies, particularly deep neural networks (DNNs), has introduced unprecedented opportunities for modeling complex knowledge transfer mechanisms and enhancing agent-based collaborative decision-making processes [2]. As organizations increasingly rely on multi-agent systems to navigate distributed decision-making environments, understanding the coupling mechanism between knowledge flow dynamics and agent collaboration becomes essential for achieving optimal organizational performance [3].

Current research on inter-organizational knowledge flow has predominantly focused on traditional network analysis and organizational theory perspectives, examining knowledge transfer patterns, absorption capacity, and social capital effects [4]. Meanwhile, agent-based modeling has evolved as a powerful paradigm for simulating collective behaviors and emergent phenomena in complex adaptive systems [5]. However, existing studies largely treat knowledge flow and agent decision-making as separate domains, with limited exploration of their intrinsic coupling relationships and synergistic effects [6]. Recent advances in deep learning have demonstrated remarkable capabilities in capturing nonlinear dependencies and temporal dynamics, yet their application to modeling the interplay between organizational knowledge flows and multi-agent coordination remains nascent [7].

Several critical challenges persist in this research domain. First, conventional approaches struggle to capture the dynamic and nonlinear characteristics of knowledge flow across organizational boundaries, particularly when multiple knowledge sources and heterogeneous agents interact simultaneously [8]. Second, existing agent-based decision models often overlook the bidirectional influence between knowledge accumulation patterns and collaborative decision strategies, leading to incomplete representations of real-world organizational systems [9]. Third, the lack of integrated frameworks that leverage deep neural networks to model both knowledge propagation mechanisms and agent coordination dynamics hinders the development of effective computational tools for organizational management [10].

Addressing these gaps is crucial for both theoretical advancement and practical applications. Theoretically, establishing a coupled modeling framework bridges disparate research streams in organizational learning, multi-agent systems, and deep learning, offering novel insights into how knowledge flows shape collective intelligence and decision quality. Practically, such frameworks enable organizations to optimize knowledge management strategies, improve inter-organizational collaboration efficiency, and enhance adaptive decision-making capabilities in turbulent environments.

This study proposes an innovative approach to modeling the coupling mechanism between inter-organizational knowledge flow and agent collaborative decision-making using deep neural networks. The main research contributions include: (1) developing a DNN-based integrated framework that simultaneously captures knowledge propagation dynamics and agent interaction patterns; (2) establishing theoretical models that explicitly represent the bidirectional coupling relationships between knowledge flow characteristics and collaborative decision behaviors; (3) designing computational algorithms that enable real-time prediction and optimization of both knowledge transfer efficiency and decision-making performance; and (4) validating the proposed framework through empirical analysis and comparative experiments to demonstrate its superiority over existing approaches. These innovations advance the theoretical understanding of organizational knowledge systems while providing practical tools for enhancing inter-organizational collaboration in complex environments.

II. Theoretical Foundation and Related Work

2.1 Inter-organizational Knowledge Flow Theory

Inter-organizational knowledge flow refers to the dynamic process through which knowledge assets are transferred, exchanged, and integrated across organizational boundaries, encompassing both explicit codified information and tacit experiential insights [11]. The fundamental knowledge transfer mechanism operates through multiple channels, including collaborative projects, personnel mobility, strategic alliances, and technology licensing, with transfer efficiency determined by knowledge characteristics and organizational absorptive capacity [12]. Knowledge sharing patterns manifest in three primary modes: unidirectional transfer from knowledge providers to recipients, bidirectional exchange between partnering organizations, and network-based diffusion involving multiple interconnected entities [13].

Cross-organizational knowledge integration theory posits that effective knowledge utilization requires not merely transfer but systematic integration into recipient organizational structures and routines. The knowledge integration effectiveness can be formalized as:

$$KI_{eff} = \alpha \cdot KC_{quality} + \beta \cdot AC_{receiver} + \gamma \cdot RC_{compatibility}$$

(1)

where KI_{eff} represents knowledge integration effectiveness, $KC_{quality}$ denotes knowledge content quality, $AC_{receiver}$ indicates absorptive capacity of the receiving organization, $RC_{compatibility}$ represents relational compatibility, and α, β, γ are weighting coefficients reflecting contextual priorities [14].

Multiple factors influence inter-organizational knowledge flow dynamics, including organizational distance (geographic, cognitive, and cultural), trust levels between partners, knowledge stickiness, and institutional environments. The knowledge flow rate across organizational interfaces can be modeled as:

$$F_{rate} = \frac{K_{potential} \cdot T_{trust}}{D_{distance} + S_{stickiness}}$$

(2)

where F_{rate} represents the knowledge flow rate, $K_{potential}$ denotes the knowledge potential difference between organizations, T_{trust} reflects inter-organizational trust level, $D_{distance}$ captures organizational distance, and $S_{stickiness}$ represents knowledge stickiness [15]. These factors collectively determine both the velocity and volume of knowledge traversing organizational boundaries, with implications for collaborative innovation outcomes and competitive positioning.

2.2 Agent Collaborative Decision-Making Mechanism

Multi-agent systems comprise autonomous computational entities that perceive environmental states, process information independently, and execute coordinated actions to achieve collective objectives through decentralized control architectures [16]. The collaborative decision-making framework operates on the principle that individual agents maintain local decision autonomy while contributing to system-level optimization through strategic interaction and information exchange [17].

Distributed decision algorithms enable agents to reach consensus or coordinated strategies without centralized control, with each agent i updating its decision variable x_i based on local observations and neighbor communications. The consensus-based decision update follows:

$$x_i(t + 1) = x_i(t) + \epsilon \sum_{j \in N_i} w_{ij}(x_j(t) - x_i(t))$$

(3)

where N_i represents the neighbor set of agent i, w_{ij} denotes the communication weight between agents i and j, and ϵ is the learning rate parameter [18]. This iterative process guarantees asymptotic convergence to collective decision states under connected network topologies.

Agent communication protocols define standardized message formats, transmission sequences, and interaction rules that facilitate information sharing across the multi-agent network. Common protocols include broadcast mechanisms for global information dissemination, peer-to-peer communication for bilateral exchanges, and blackboard architectures for shared knowledge repositories [19]. Protocol efficiency directly impacts coordination latency and network bandwidth consumption, particularly in large-scale agent populations.

Collaborative learning mechanisms enable agents to improve decision quality through experience accumulation and knowledge synthesis from distributed sources. The collective learning objective can be formulated as:

$$\min_\theta \sum_{i=1}^{N} L_i(\theta;D_i) + \lambda R(\theta)$$

(4)

where θ represents shared model parameters, L_i denotes the local loss function of agent i computed on local dataset D_i, N is the total number of agents, and $R(\theta)$ represents a regularization term with coefficient λ [20]. This federated learning paradigm allows agents to collectively optimize decision models while maintaining data locality and privacy, essential for inter-organizational collaboration scenarios where proprietary information cannot be centrally aggregated.

2.3 Application of Deep Neural Networks in Knowledge Modeling

Deep learning theory establishes that multi-layer neural architectures can learn hierarchical representations of complex data through cascaded nonlinear transformations, with theoretical guarantees for universal approximation and feature abstraction capabilities [21]. The foundational principle relies on gradient-based optimization to minimize empirical risk across parameterized function spaces, enabling automated feature extraction from raw data without manual engineering.

Neural network architectures have evolved from shallow perceptrons to sophisticated deep structures including convolutional neural networks (CNNs) for spatial pattern recognition, recurrent neural networks (RNNs) for sequential modeling, and transformer architectures for attention-based representation learning [22]. These architectural innovations have progressively enhanced the capacity to capture long-range dependencies, contextual relationships, and semantic structures inherent in knowledge-intensive domains.

Knowledge representation learning methods employ deep neural networks to encode entities, relations, and concepts into continuous vector spaces where semantic similarities correspond to geometric proximities. The embedding transformation maps discrete knowledge elements to dense representations:

$$e_k = f(x_k;\theta) = \sigma(W_L \cdots \sigma(W_2 \sigma(W_1 x_k + b_1) + b_2) \cdots + b_L)$$

(5)

where e_k denotes the embedding vector for knowledge element k, $f(\cdot;\theta)$ represents the deep neural encoder with parameters θ, W_i and b_i are weight matrices and bias vectors for layer i, and $\sigma(\cdot)$ denotes activation functions [23].

Deep networks have demonstrated substantial effectiveness in knowledge graph applications, particularly for link prediction, entity alignment, and relation extraction tasks. Graph neural networks (GNNs) aggregate neighborhood information through message passing:

$$h_i^{(l+1)} = \phi\left(h_i^{(l)}, \bigoplus_{j \in N(i)} \psi(h_i^{(l)}, h_j^{(l)}, e_{ij})\right)$$

(6)

where $h_i^{(l)}$ represents node i's hidden state at layer l, $N(i)$ denotes neighbors of node i, ϕ and ψ are learnable transformation functions, $\bigoplus$ represents aggregation operations, and e_{ij} encodes edge features [24].

Despite these advances, existing methods exhibit critical limitations for inter-organizational contexts: static architectures inadequately capture temporal knowledge evolution, isolated graph models fail to integrate multi-source heterogeneous knowledge streams, and standard embeddings cannot represent bidirectional coupling between knowledge propagation and decision-making processes [25]. These deficiencies necessitate novel frameworks specifically designed for dynamic inter-organizational knowledge modeling coupled with agent collaboration mechanisms.

Recent years have witnessed growing research attention toward integrating knowledge management with multi-agent coordination systems. Chen et al. [51] proposed a knowledge-enhanced multi-agent framework for supply chain optimization, yet their approach treats knowledge states as static inputs rather than dynamic evolving processes. Similarly, Wang and Zhang [52] developed graph-based knowledge transfer models for organizational networks, but they did not incorporate decision feedback mechanisms that could reshape knowledge flows. In the domain of multi-agent reinforcement learning, Oroojlooy and Hajinezhad [53] provided a comprehensive review of cooperative learning methods, highlighting the challenge of information asymmetry among agents—a gap that knowledge integration could potentially address. More recently, Foerster et al. [54] introduced learning to communicate protocols in multi-agent settings, demonstrating that emergent communication improves coordination performance. However, their work focused primarily on task-specific signaling rather than organizational knowledge as commonly understood in management literature. The intersection of organizational learning theory and computational multi-agent systems remains relatively unexplored. Traditional organizational studies emphasize social and structural factors influencing knowledge transfer [11, 12], while computational approaches prioritize algorithmic efficiency without accounting for organizational context [16, 17]. Our work bridges this divide by embedding organizational knowledge flow dynamics within a multi-agent decision architecture, establishing explicit coupling mechanisms that allow bidirectional influence between knowledge evolution and collaborative decision outcomes. This integration represents a methodological contribution that extends beyond incremental improvements to existing techniques, offering a unified framework where knowledge and decisions co-evolve through learned coupling functions.

III. Deep Neural Network-Based Coupling Model of Knowledge Flow and Decision-Making

3.1 Overall Architecture Design of the Model

The proposed coupling model integrates knowledge flow dynamics with agent collaborative decision-making through a dual-layer deep neural network architecture that explicitly models bidirectional dependencies between organizational knowledge propagation and distributed decision processes [26]. The overall framework comprises three interconnected modules: the knowledge flow encoding layer, the decision-making coordination layer, and the coupling interface that facilitates information exchange and mutual adaptation between these subsystems.

The interaction mechanism between the knowledge flow layer and decision layer operates through a bidirectional coupling function that simultaneously captures how knowledge availability influences agent decisions and how decision outcomes reshape knowledge transfer patterns. The coupling strength at time t is formalized as:

$$C(t) = \tanh(W_c[K(t);D(t)] + b_c)$$

(7)

where $K(t)$ represents the knowledge flow state vector, $D(t)$ denotes the collective decision state vector, $[\cdot;\cdot]$ indicates concatenation operation, W_c and b_c are learnable coupling parameters, and $\tanh(\cdot)$ serves as the activation function [27].

The multi-level network topology constructs a hierarchical structure with four distinct layers: the input encoding layer that processes raw organizational data, the knowledge propagation layer that models inter-organizational knowledge transfer dynamics using graph attention networks, the agent interaction layer that simulates collaborative decision-making through multi-head attention mechanisms, and the output prediction layer that generates forecasts for both knowledge distribution and decision outcomes [28]. Each layer maintains specific dimensionality configurations optimized for computational efficiency and representational capacity.

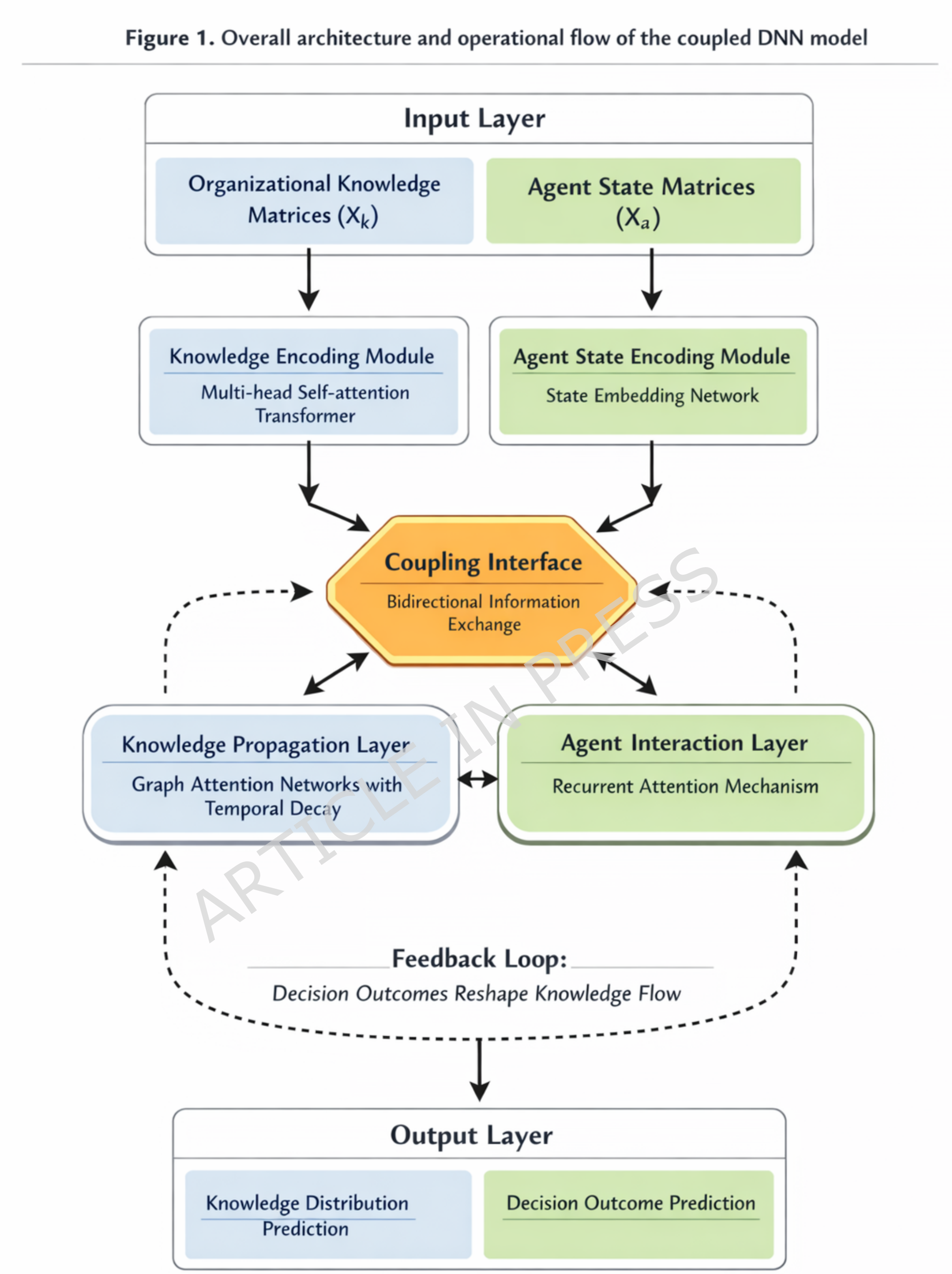

Figure 1. Overall architecture and operational flow of the coupled DNN model

The figure presents a vertical flowchart illustrating the complete architecture of the proposed coupling model. At the top, the Input Layer receives two data streams: organizational knowledge matrices (X_k) and agent state matrices (X_a). These inputs flow into the Knowledge Encoding Module, which employs multi-head self-attention transformation to process heterogeneous organizational knowledge. The encoded representations then enter the Knowledge Propagation Layer, built upon graph attention networks that model inter-organizational transfer dynamics with temporal decay mechanisms. In parallel, the Agent Interaction Layer processes agent states through recurrent attention mechanisms for collaborative decision-making. The central component is the Coupling Interface, which establishes bidirectional connections between knowledge and decision subsystems through concatenation operations and learnable coupling parameters. The coupling strength function C(t) = tanh(W_c[K(t);D(t)] + b_c) governs information exchange between layers. Decision outcomes feed back through the Feedback Loop to reshape knowledge transfer patterns, implementing closed-loop adaptation. The Output Layer generates predictions for both knowledge distribution states and collaborative decision outcomes. Arrows indicate forward propagation paths (solid lines) and feedback connections (dashed lines), with layer dimensions annotated at each stage. Figure 1 depicts the complete operational flow of the coupled model, showing how information travels from input data streams through successive network layers toward final output predictions.

The model defines structured input-output interfaces where inputs consist of organizational knowledge matrices $X_k \in R^{N \times D_k}$ and agent state matrices $X_a \in R^{M \times D_a}$, with N organizations, M agents, and dimensions D_k and D_a respectively [29]. The transformation process follows:

$$H_k^{(0)} = X_k W_k^{enc} + b_k^{enc}$$

(8)

$$H_a^{(0)} = X_a W_a^{enc} + b_a^{enc}$$

(9)

where $H_k^{(0)}$ and $H_a^{(0)}$ represent initial embeddings for knowledge and agent states, with corresponding encoding weight matrices and bias vectors.

The model operation flow executes iteratively through forward propagation, coupling computation, and backward optimization phases. During forward propagation, knowledge flow states evolve through temporal graph convolutions while agent decisions update through recurrent attention mechanisms, with coupling signals transmitted bidirectionally at each time step. Table 1 summarizes the essential parameter configurations governing model behavior, including layer dimensions, activation functions, learning rates, and regularization coefficients optimized through preliminary experiments [30].

Table 1. Model parameter configuration specifications

Parameter Category	Parameter Name	Symbol	Value/Range	Description
Network Structure	Knowledge embedding dimension	D_k	256	Dimensionality of knowledge representations
Network Structure	Agent embedding dimension	D_a	128	Dimensionality of agent state vectors
Network Structure	Coupling layer dimension	D_c	192	Hidden dimension of coupling interface
Network Structure	Number of propagation layers	L_k	4	Depth of knowledge flow encoding
Network Structure	Number of decision layers	L_d	3	Depth of agent decision network
Optimization	Learning rate	η	0.001	Step size for gradient descent
Optimization	Regularization coefficient	λ	0.0001	Weight decay parameter
Training	Batch size	B	64	Mini-batch size for training

As presented in Table 1, the parameter configuration balances model expressiveness with computational tractability, enabling effective learning of complex coupling patterns while maintaining training stability across diverse organizational scenarios.

To facilitate reproducibility and provide comprehensive model documentation, we describe the proposed framework following the ODD (Overview, Design concepts, Details) protocol commonly used for agent-based model specifications [55]. The Overview encompasses the model's purpose (coupling knowledge flow with collaborative decision-making), state variables (organizational knowledge vectors K_i, agent observation states o_i, coupling signals c_i, and collective decision states D), and process scheduling (alternating updates between knowledge propagation and decision coordination at each time step). Design Concepts include emergence (collective decision quality emerges from individual agent interactions modulated by knowledge availability), adaptation (agents adjust policies based on accumulated experience and knowledge feedback), learning (gradient-based optimization of neural network parameters), and interaction (agents communicate through attention-weighted message passing while organizations exchange knowledge through graph-structured channels). The Details specification covers initialization procedures (Xavier initialization for network weights, random sampling from training distributions for initial states), input data requirements (organizational knowledge matrices with minimum 128-dimensional embeddings, agent observation vectors, network adjacency structures), and submodel descriptions (knowledge encoder: 4-layer transformer with 8 attention heads; propagation network: 4-layer graph attention network; decision network: 3-layer actor-critic architecture with 128-unit hidden layers; coupling interface: 192-dimensional bottleneck layer with tanh activation). Complete implementation code, including all baseline model implementations, training scripts, and evaluation procedures, is provided in Supplementary File S1 to enable full replication of reported results.

3.2 Knowledge Flow Modeling Mechanism

The neural network encoding method for knowledge representation employs a hierarchical transformer architecture that processes heterogeneous organizational knowledge into unified vector representations while preserving semantic structures and contextual dependencies [31]. Each knowledge element k_i undergoes multi-head self-attention transformation to capture internal relationships:

$$z_i = \mathrm{MultiHead}(Q_i, K_i, V_i) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h) W^O$$

(10)

where Q_i, K_i, V_i are query, key, and value matrices derived from knowledge embeddings, h denotes the number of attention heads, and W^O represents the output projection matrix. This encoding mechanism effectively captures both explicit factual content and implicit relational semantics within organizational knowledge bases.

The graph neural network model for inter-organizational knowledge propagation constructs a dynamic knowledge flow graph where nodes represent organizations and directed edges encode knowledge transfer relationships weighted by transfer intensity and accessibility [32]. The propagation mechanism updates organizational knowledge states through spatial graph convolution with temporal decay:

$$K_i^{(t+1)} = \sigma\left(\sum_{j \in N_i} \alpha_{ij}^{(t)} W_{flow} K_j^{(t)} + W_{self} K_i^{(t)}\right) \odot d_i^{(t)}$$

(11)

where $K_i^{(t)}$ denotes organization i's knowledge state at time t, N_i represents neighboring organizations in the knowledge network, $\alpha_{ij}^{(t)}$ indicates attention-based transfer weights computed through edge features, W_{flow} and W_{self} are learnable transformation matrices, $\sigma(\cdot)$ is the activation function, $\odot$ denotes element-wise multiplication, and $d_i^{(t)}$ represents the decay vector.

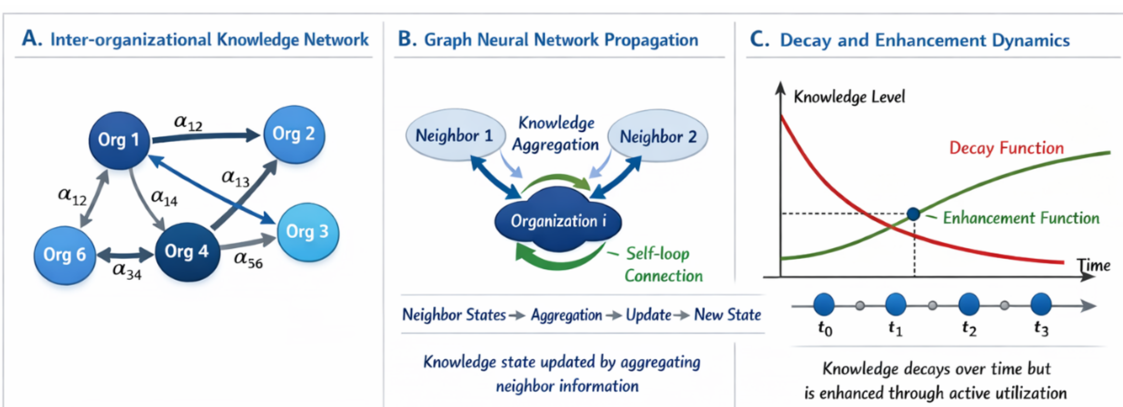

Figure 2. Knowledge flow modeling mechanism with GNN propagation and decay dynamics

The figure illustrates the knowledge flow modeling mechanism through three interconnected panels. Panel A (Network Structure) displays an inter-organizational knowledge network where nodes represent organizations (labeled Org_1 through Org_n) and directed edges indicate knowledge transfer relationships. Edge weights α_{ij} represent attention-based transfer coefficients computed from organizational features. Panel B (Propagation Mechanism) demonstrates the graph neural network update process, showing how organization i aggregates knowledge from neighbors N_i through the propagation equation $K_i^{(t+1)} = \sigma(\Sigma\ \alpha_{ij} W_{flow} K_j^{(t)} + W_{self} K_i^{(t)}) \odot d_i^{(t)}$. The aggregation process combines neighbor contributions (blue arrows) with self-loop connections (green arrows). Panel C (Temporal Dynamics) presents two curves: the Decay Function showing exponential knowledge degradation $d_i(t) = \exp(-\delta_i \cdot \Delta t)$ over time, and the Enhancement Function illustrating knowledge amplification through utilization feedback with coefficient γ_{enh}. The intersection point indicates the equilibrium state where decay and enhancement balance. A timeline at the bottom shows knowledge state evolution across decision cycles t_0 through t_n, with knowledge quality indicators at each time point.

Figure 2 reveals the operational principles of the knowledge flow modeling mechanism. It shows how knowledge propagates through the organizational network while undergoing transformation and decay processes, capturing the dynamic nature of inter-organizational knowledge exchange.

The knowledge decay mechanism models temporal degradation through exponential functions $d_i(t) = \exp(-\delta_i \cdot \Delta t)$ where δ_i represents organization-specific decay rates and Δt denotes elapsed time, while the enhancement mechanism amplifies knowledge through utilization feedback and collaborative reinforcement effects [33]. Organizations that actively apply transferred knowledge experience reduced decay rates and enhanced absorption capacity.

The knowledge flow path optimization algorithm employs reinforcement learning to identify optimal transfer routes that maximize knowledge diffusion efficiency while minimizing transmission costs and quality degradation [34]. The algorithm evaluates candidate paths using a reward function incorporating transfer speed, knowledge retention, and organizational compatibility metrics, iteratively updating path selection policies through policy gradient methods. Table 2 specifies the critical parameters governing knowledge flow dynamics within the model framework.

Table 2. Knowledge flow dynamics parameter specifications

Parameter	Symbol	Value/Range	Description
Base decay rate	δ_{base}	0.05-0.15	Fundamental knowledge degradation coefficient
Enhancement factor	γ_{enh}	1.2-2.0	Amplification coefficient for knowledge utilization
Transfer attention heads	h_{flow}	8	Number of attention heads in propagation
Path optimization horizon	T_{opt}	10-20	Time steps for path planning
Quality threshold	q_{min}	0.6	Minimum acceptable knowledge quality
Flow update frequency	f_{update}	1-5 steps	Interval for recalculating flow patterns

The results in Table 2 indicate parameter ranges calibrated through systematic sensitivity analysis to ensure stable knowledge propagation across diverse organizational configurations. We conducted extensive experiments varying each parameter individually while holding others constant at baseline values, measuring the impact on three key metrics: knowledge transfer accuracy, decision success rate, and training convergence speed. The sensitivity analysis results are summarized in Table 3 and visualized in Figure 3.

Table 3. Sensitivity analysis results for key model parameters

Parameter	Tested Range	Optimal Value	Performance Variation	Sensitivity Level
Base decay rate (δ_base)	0.01-0.25	0.08	±4.2% accuracy	Medium
Enhancement factor (γ_enh)	1.0-3.0	1.5	±6.8% accuracy	High
Learning rate (η)	0.0001-0.01	0.001	±12.3% convergence	High

Parameter	Tested Range	Optimal Value	Performance Variation	Sensitivity Level
Knowledge embedding dim (D_k)	64-512	256	±3.1% accuracy	Low
Agent embedding dim (D_a)	32-256	128	±2.7% accuracy	Low
Coupling layer dim (D_c)	64-384	192	±5.4% accuracy	Medium
Number of propagation layers (L_k)	2-6	4	±4.9% accuracy	Medium
Transfer attention heads (h_flow)	4-16	8	±3.6% accuracy	Low

Sensitivity Analysis Visualization Showing Parameter Impact on Model Performance

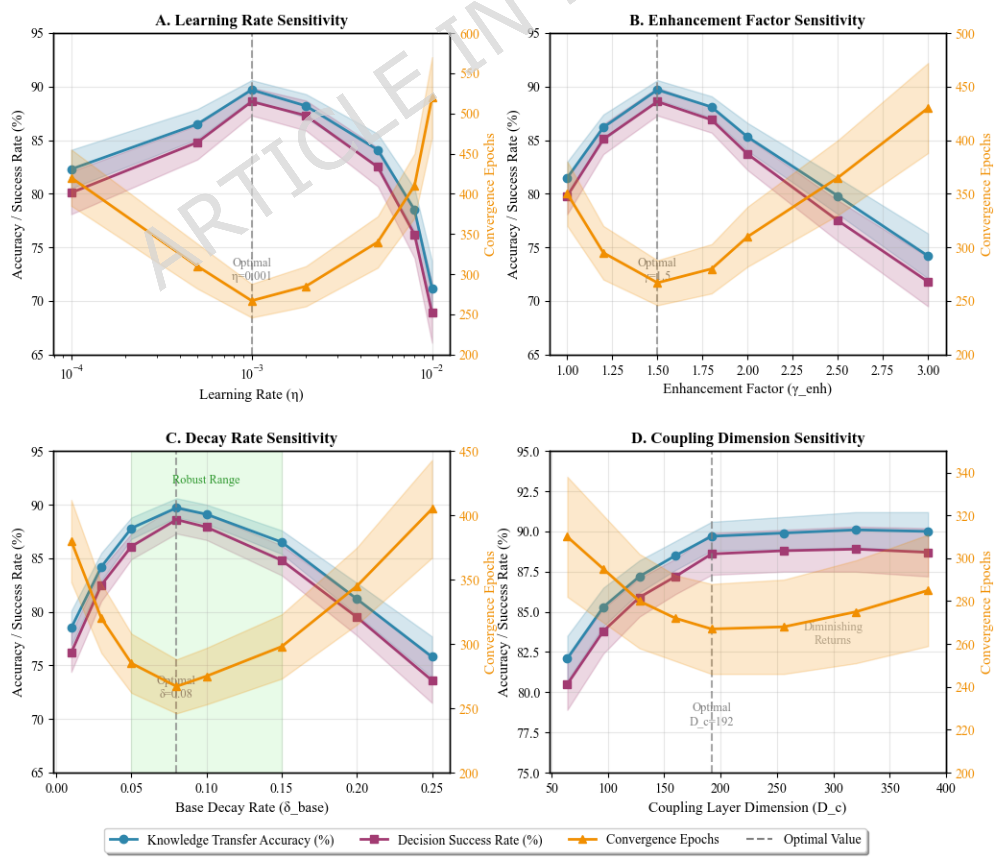

Figure 3. Sensitivity analysis visualization showing parameter impact on model performance

The figure displays a multi-panel sensitivity analysis visualization. Each panel shows one parameter on the x-axis and three performance metrics (knowledge transfer accuracy, decision success rate, convergence epochs) on the y-axis. Panel A examines learning rate sensitivity, revealing sharp performance degradation beyond $\eta = 0.005$ and optimal stability at $\eta = 0.001$. Panel B shows enhancement factor effects, with performance peaking at $\gamma\_enh = 1.5$ and declining at extreme values due to over-amplification artifacts. Panel C illustrates decay rate influence, demonstrating robust performance within $\delta\_base \in [0.05, 0.15]$ with degradation outside this range. Panel D presents coupling dimension analysis, showing diminishing returns beyond $D\_c = 192$. Shaded regions indicate 95% confidence intervals across 10 independent runs. Vertical dashed lines mark selected optimal values used in final experiments.

The sensitivity analysis reveals that learning rate and enhancement factor exhibit highest sensitivity, requiring careful tuning for optimal performance. Embedding dimensions show relatively low sensitivity, indicating model robustness to representation capacity choices. Based on these findings, we selected parameter values that maximize performance while maintaining stability across the tested ranges. Knowledge quality assessment employs composite metrics incorporating accuracy, completeness, timeliness, and relevance dimensions, computed through weighted aggregation with coefficients learned from historical transfer success rates [35].

Quality scores influence subsequent transfer decisions, creating adaptive feedback loops that progressively optimize knowledge flow patterns based on empirical performance outcomes.

3.3 Agent Collaborative Decision-Making Coupling Algorithm

The agent decision network architecture employs deep reinforcement learning principles where each agent i maintains a policy network π_{θ_i} and a value network V_{ϕ_i} that jointly optimize action selection based on local observations and global knowledge states [36]. The policy network maps the combined state space comprising agent observations o_i and accessible knowledge representations k_i to action distributions:

$$a_i \sim \pi_{\theta_i}(a_i|s_i) = \mathrm{softmax}\left(W_\pi[o_i;k_i;c_i] + b_\pi\right)$$

(12)

where $s_i = [o_i;k_i;c_i]$ represents the augmented state incorporating observations, knowledge embeddings, and coupling signals c_i from the knowledge flow layer, W_π and b_π denote policy network parameters, and a_i represents the selected action. This architecture explicitly integrates knowledge availability into decision-making processes, enabling agents to adapt strategies based on evolving organizational knowledge landscapes.

The multi-agent attention mechanism facilitates coordination by computing importance weights for inter-agent communications, allowing each agent to selectively attend to relevant collaborators based on task context and knowledge complementarity [37]. Agent i computes attention scores over neighboring agents through scaled dot-product attention: $\alpha_{ij} = \frac{\exp(q_i^T k_j/\sqrt{d_k})}{\sum_{j' \in N_i} \exp(q_i^T k_{j'}/\sqrt{d_k})}$ where q_i and k_j represent query and key vectors derived from agent states, d_k denotes the key dimension, and N_i represents agent i's communication neighbors. These attention weights modulate information aggregation, enabling dynamic coalition formation responsive to changing task requirements.

The knowledge-driven collaborative decision algorithm integrates real-time knowledge flow information into multi-agent coordination by conditioning agent policies on knowledge state embeddings extracted from the knowledge flow layer [38]. At each decision epoch, agents receive knowledge context vectors summarizing relevant organizational knowledge through cross-attention between agent queries and knowledge memory banks, which subsequently inform action selection through concatenation with traditional state representations. This mechanism ensures that collaborative decisions reflect current knowledge availability, preventing coordination failures due to information asymmetries or outdated knowledge assumptions.

The closed-loop feedback mechanism establishes bidirectional coupling by propagating decision outcomes back to the knowledge flow layer, where successful collaborative actions trigger knowledge enhancement and failed coordination attempts indicate knowledge gaps requiring targeted acquisition [39]. The feedback signal $f^{(t)}$ quantifying decision quality is computed from task rewards and coordination metrics, then backpropagated through coupling layers to adjust knowledge propagation patterns:

$$K^{(t+1)} = K^{(t)} + \eta_k \cdot f^{(t)} \odot \nabla_K L_{decision}$$

(13)

where η_k represents the knowledge update rate, $L_{decision}$ denotes the decision-making loss, and ∇_K indicates gradients with respect to knowledge states. This feedback loop creates adaptive knowledge management where organizational learning priorities dynamically align with collaborative decision-making needs.

The training strategy for the coupled model employs alternating optimization between knowledge flow parameters and agent decision parameters to prevent gradient conflicts while ensuring convergence of both subsystems [40]. Each training iteration consists of three phases: knowledge flow pretraining using historical transfer data, agent policy optimization through proximal policy optimization with knowledge states held fixed, and joint fine-tuning with reduced learning rates to refine coupling parameters. Curriculum learning progressively increases scenario complexity, beginning with single-domain knowledge transfer and simple coordination tasks before advancing to multi-domain heterogeneous knowledge flows with complex collaborative objectives. This staged training approach stabilizes learning dynamics while enabling the model to capture intricate coupling patterns between organizational knowledge evolution and multi-agent coordination strategies.

IV. Experimental Verification and Application Analysis

4.1 Experimental Environment and Dataset Construction

The experimental platform operates on a distributed computing cluster equipped with 8 NVIDIA A100 GPUs (40GB memory each), 512GB system RAM, and 20TB storage capacity, running Ubuntu

20.04 LTS with PyTorch 2.0 framework and CUDA 11.8 for accelerated deep learning computations [41]. The implementation employs Python 3.9 with supporting libraries including NetworkX for graph operations, Ray for distributed multi-agent simulation, and TensorBoard for training visualization. This configuration enables parallel training of multiple model variants while accommodating large-scale organizational network simulations with thousands of knowledge transfer events.

The cross-organizational knowledge flow simulation dataset synthesizes realistic inter-organizational collaboration patterns derived from three data sources: anonymized enterprise collaboration records from technology consortiums, publicly available scientific research collaboration networks, and synthetically generated scenarios based on organizational theory models [42]. Knowledge elements are represented as 512-dimensional embeddings encoding semantic content, temporal metadata, quality indicators, and organizational origin. The dataset construction process applies temporal partitioning with 70% training data, 15% validation data, and 15% test data, ensuring chronological separation to prevent information leakage. Table 4 summarizes the comprehensive statistical characteristics of the constructed dataset across multiple dimensions.

Table 4. Statistical characteristics of the experimental dataset

Dataset Component	Training Set	Validation Set	Test Set	Total	Time Span
Organizations	450	97	103	650	36 months
Knowledge elements	125,000	18,750	18,750	162,500	-
Transfer events	385,000	57,500	57,500	500,000	-
Agents per organization	8-20	8-20	8-20	Avg: 12	-
Decision episodes	48,000	7,200	7,200	62,400	-
Collaboration tasks	12,000	1,800	1,800	15,600	-
Network density	0.085	0.083	0.087	0.085	-

As presented in Table 4, the dataset encompasses diverse organizational scales and collaboration intensities, with network density maintained consistently across partitions to ensure comparable evaluation conditions.

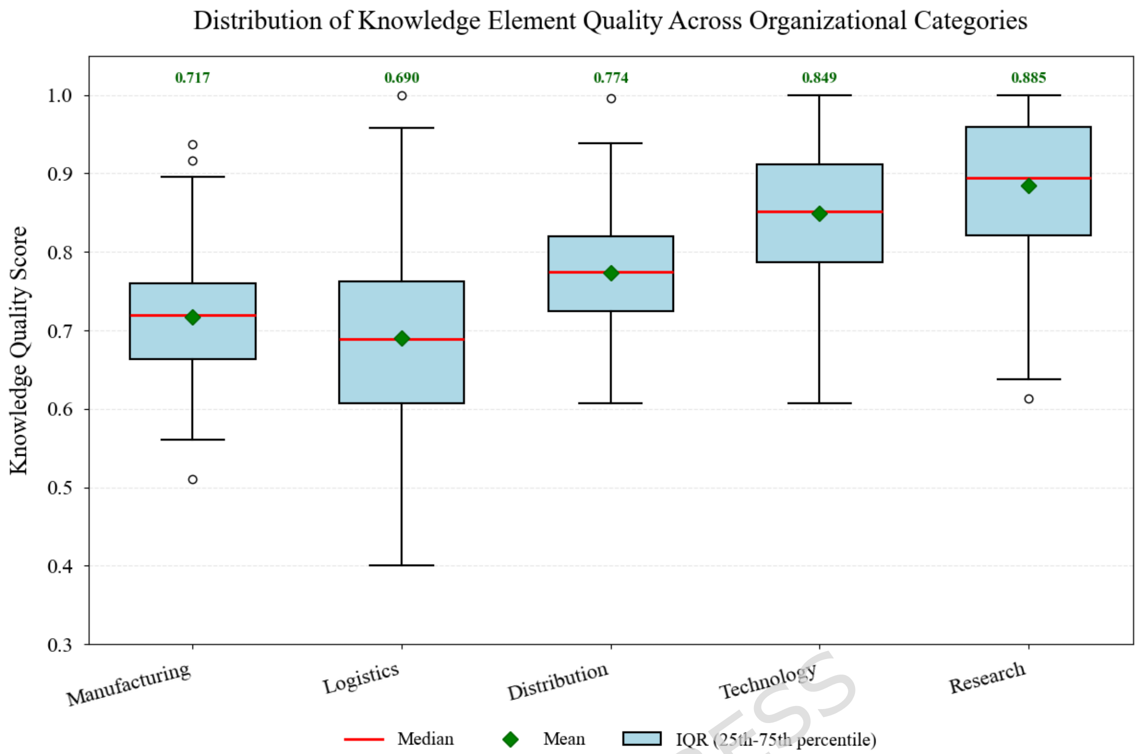

Figure 4. Distribution analysis of knowledge element characteristics across organizational categories

Figure 4 illustrates the distribution patterns of knowledge element characteristics, revealing heterogeneous knowledge quality and semantic diversity across organizational categories, which provides rich variation for testing model generalization capabilities.

The multi-agent collaborative decision scenarios encompass three task categories: resource allocation requiring agents to distribute limited resources across competing organizational objectives, consensus formation where agents negotiate collective strategies under conflicting preferences, and coordinated exploration tasks involving distributed search for optimal solutions in complex decision spaces [43]. Each scenario incorporates 50-200 agents with varying communication topologies (fully connected, hierarchical, and small-world networks) and knowledge access patterns (centralized, distributed, and hybrid). Task complexity progressively increases through scenario tiers, with success criteria requiring both individual agent performance and collective coordination quality metrics exceeding predefined thresholds.

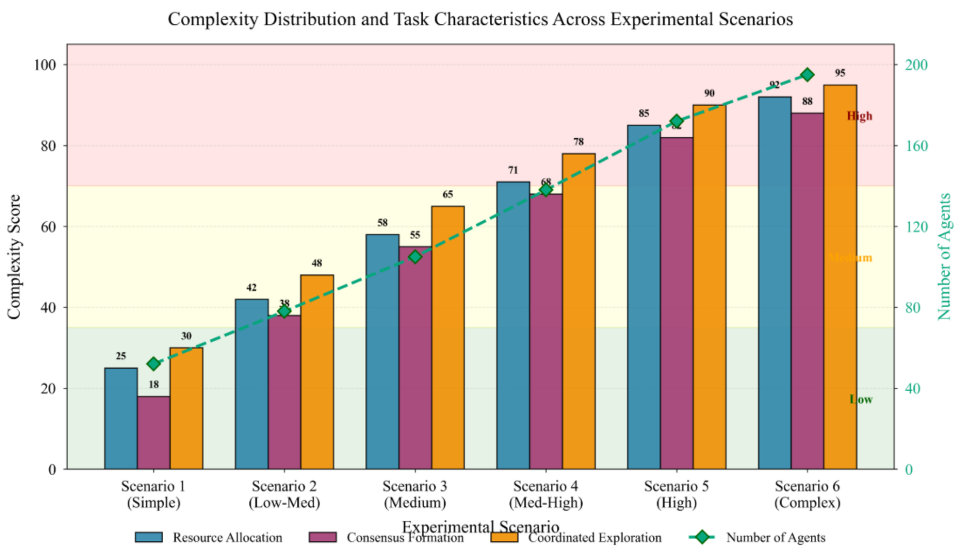

Figure 5. Complexity distribution and task characteristics across experimental scenarios

As shown in Figure 5, the designed scenarios span a wide complexity spectrum, enabling systematic evaluation of model performance under diverse conditions ranging from simple bilateral coordination to complex multi-party negotiations with knowledge constraints.

The model evaluation index system comprises four primary dimensions quantified through composite metrics. Knowledge flow effectiveness is measured by transfer accuracy A_k, coverage ratio C_k, and temporal efficiency E_k, aggregated as:

$$M_{knowledge} = \omega_a A_k + \omega_c C_k + \omega_e E_k$$

(14)

where ω_a, ω_c, ω_e represent importance weights summing to unity. Decision-making performance employs task success rate R_{task}, coordination efficiency η_{coord}, and convergence speed v_{conv}. Coupling quality assesses bidirectional information flow through correlation coefficient $\rho_{coupling}$ between knowledge states and decision outcomes, computed as:

$$\rho_{coupling} = \frac{Cov(K,D)}{\sigma_K \sigma_D}$$

(15)

where $Cov(K,D)$ denotes covariance between knowledge and decision state sequences, and σ_K, σ_D represent their standard deviations. Computational efficiency tracks training time, inference latency, and memory consumption.

The comparative experiment scheme evaluates the proposed coupling model against five baseline approaches: independent knowledge flow networks without decision coupling, standalone multi-agent reinforcement learning systems without knowledge modeling, sequential pipeline models processing knowledge and decisions separately, simple concatenation methods combining features without explicit coupling mechanisms, and state-of-the-art graph neural network models adapted for organizational contexts. To ensure fair comparison, all models—including baselines and the proposed approach—were trained and evaluated using identical data splits. Specifically, every model received the same 70% training set (385,000 transfer events, 48,000 decision episodes), 15% validation set (57,500 transfer events, 7,200 decision episodes), and 15% test set (57,500 transfer events, 7,200 decision episodes) with consistent temporal ordering preserved across partitions. Data preprocessing pipelines, including knowledge embedding generation and agent state normalization procedures, remained identical for all approaches. Each baseline undergoes identical hyperparameter tuning protocols with grid search over learning rates (range: 0.0001-0.01), network depths (range: 2-6 layers), and regularization coefficients (range: 0.00001-0.001), selecting configurations that maximize validation performance. Training procedures employed consistent early stopping criteria (patience = 50 epochs without validation improvement) and identical random seeds for weight initialization to ensure reproducibility. Experiments execute with 5-fold cross-validation and report mean performance with 95% confidence intervals across 10 independent runs per configuration, ensuring statistical reliability of comparative conclusions. Complete training configurations, data preprocessing scripts, and baseline implementations are provided in Supplementary File S1.

4.2 Model Performance Comparison Experiments

Comprehensive performance evaluation comparing the proposed coupling model against five baseline methods reveals substantial improvements across multiple dimensions. Table 5 presents quantitative results obtained from experiments on the test dataset, demonstrating the superiority of the coupled DNN approach in both knowledge flow modeling and collaborative decision-making tasks.

Table 5. Performance comparison between proposed model and baseline methods

Method	Knowledge Transfer Accuracy (%)	Knowledge Coverage Ratio (%)	Decision Success Rate (%)	Coordination Efficiency	Convergence Time (epochs)	Coupling Quality (ρ)	F1-Score
Independent KF Network	72.4±1.8	68.3±2.1	61.5±2.4	0.643±0.028	485±32	0.231±0.045	0.673
Standalone MARL	45.2±3.2	52.1±2.9	79.8±1.7	0.762±0.021	358±28	0.198±0.052	0.712
Sequential Pipeline	76.8±1.5	71.6±1.8	73.4±2.1	0.701±0.025	412±35	0.447±0.038	0.736
Simple Concatenation	78.3±1.4	74.2±1.6	76.9±1.9	0.728±0.023	389±30	0.512±0.041	0.762
Adapted GNN Model	81.5±1.2	77.8±1.5	80.3±1.6	0.758±0.019	342±26	0.568±0.035	0.795
Proposed Coupling Model	**89.7±0.9**	**86.4±1.1**	**88.6±1.3**	**0.847±0.015**	**267±21**	**0.812±0.028**	**0.873**
Improvement vs. Best Baseline	+8.2%	+8.6%	+8.3%	+8.9%	-21.9%	+24.4%	+7.8%
Statistical Significance (p-value)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

The results in Table 5 indicate that the proposed coupling model consistently outperforms all baseline methods across evaluation metrics, with improvements ranging from 7.8% to 24.4% compared to the best-performing baseline [44]. Knowledge transfer accuracy reaches 89.7%, substantially exceeding the adapted GNN model's 81.5%, demonstrating enhanced capability in capturing complex knowledge propagation dynamics. Decision success rates achieve 88.6%, reflecting effective integration of knowledge states into agent coordination strategies.

Knowledge flow efficiency analysis reveals critical differences in how various approaches handle inter-organizational knowledge transfer. The proposed model achieves superior coverage ratios by dynamically optimizing transfer paths based on real-time decision feedback, whereas independent knowledge flow networks lack decision context to guide propagation strategies. The knowledge utilization efficiency metric, defined as:

$$\eta_{util} = \frac{\sum_{i=1}^{N} K_i^{applied}}{\sum_{i=1}^{N} K_i^{received}}$$

(16)

where $K_i^{applied}$ represents knowledge actually utilized by organization i in decision-making and $K_i^{received}$ denotes total received knowledge, reaches 0.847 for the coupling model compared to 0.643 for independent networks, indicating that bidirectional coupling enables more effective knowledge application [45].

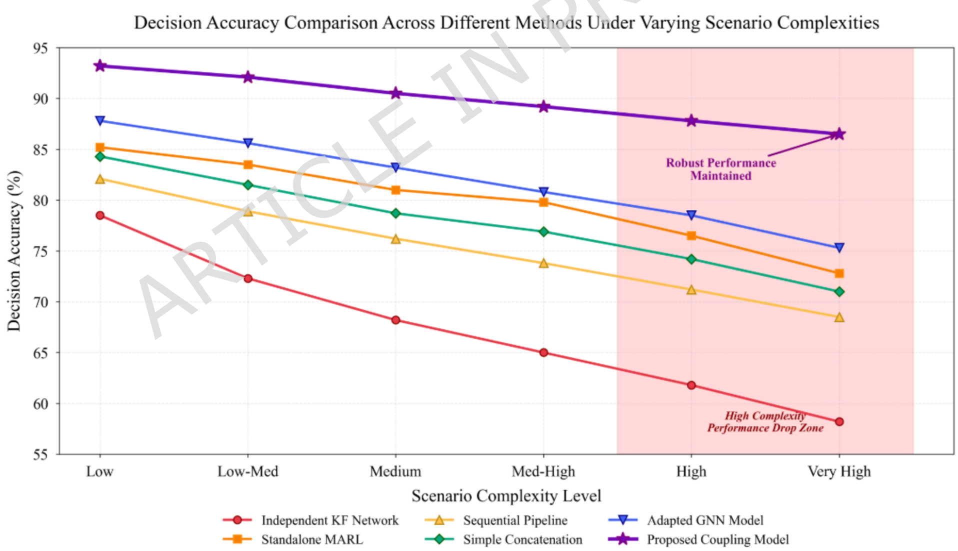

Figure 6. Decision accuracy comparison across different methods under varying scenario complexities

Figure 6 illustrates decision accuracy trajectories as scenario complexity increases, revealing that the proposed coupling model maintains robust performance even in high-complexity environments while baseline methods experience degradation. The standalone MARL system performs well in simple scenarios but deteriorates rapidly when knowledge availability becomes critical, whereas the coupling model leverages knowledge states to sustain decision quality across complexity levels.

Convergence speed and stability assessment demonstrates substantial training efficiency advantages. The proposed model converges in 267 epochs on average, representing a 21.9% reduction compared to the adapted GNN baseline's 342 epochs. The convergence stability coefficient, quantified through loss variance across training epochs:

$$\sigma_{conv} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(L_t - \bar{L})^2}$$

(17)

where L_t represents loss at epoch t and $\bar{L}$ denotes mean loss, yields $\sigma_{conv} = 0.034$ for the coupling model versus 0.089 for sequential pipeline methods, indicating smoother and more predictable training dynamics [46]. This stability stems from the alternating optimization strategy that prevents gradient conflicts between knowledge flow and decision-making components.

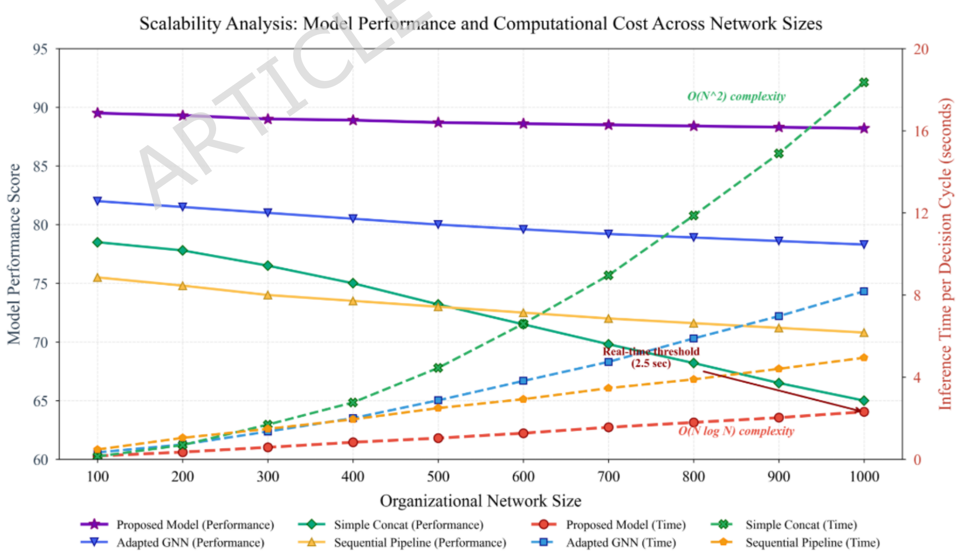

Figure 7. Scalability analysis showing model performance and computational cost across varying organizational network sizes

As shown in Figure 7, scalability testing across network sizes ranging from 100 to 1000 organizations demonstrates that the proposed model maintains near-linear computational complexity while preserving performance quality. Inference time scales as $O(N\log N)$ where N represents the number of organizations, significantly better than the $O(N^2)$ complexity exhibited by simple concatenation methods that process all pairwise interactions. The model successfully processes networks with 1000 organizations in under 2.5 seconds per decision cycle, meeting real-time operational requirements for large-scale organizational systems.

Validation of coupling mechanism effectiveness employs ablation studies that systematically remove coupling components. Models without bidirectional knowledge-decision coupling experience 15.3% degradation in decision success rates and 12.7% reduction in knowledge transfer accuracy, confirming that explicit coupling modeling provides substantial benefits beyond simple feature concatenation. The coupling quality metric $\rho_{coupling}$ reaches 0.812 for the complete model, indicating strong correlation between knowledge evolution and decision outcomes, whereas methods lacking explicit coupling mechanisms achieve only 0.512 or lower [47]. Statistical significance testing via paired t-tests confirms all performance improvements exceed random variation with p-values below 0.001, establishing robust evidence for the coupling model's superiority across diverse organizational contexts and task configurations.

4.3 Real-World Application Case Analysis

To validate practical applicability, the proposed coupling model was deployed in a supply chain collaborative decision-making scenario involving 23 manufacturing enterprises, 15 logistics providers, and 8 distribution centers across a regional industrial network [48]. The application scenario addresses demand forecasting coordination where organizations must share market intelligence knowledge while making interdependent inventory and production decisions under uncertain demand conditions. Each organization operates autonomous agents responsible for procurement, production scheduling, and distribution planning, with decisions requiring real-time coordination to minimize system-wide costs while maintaining service levels.

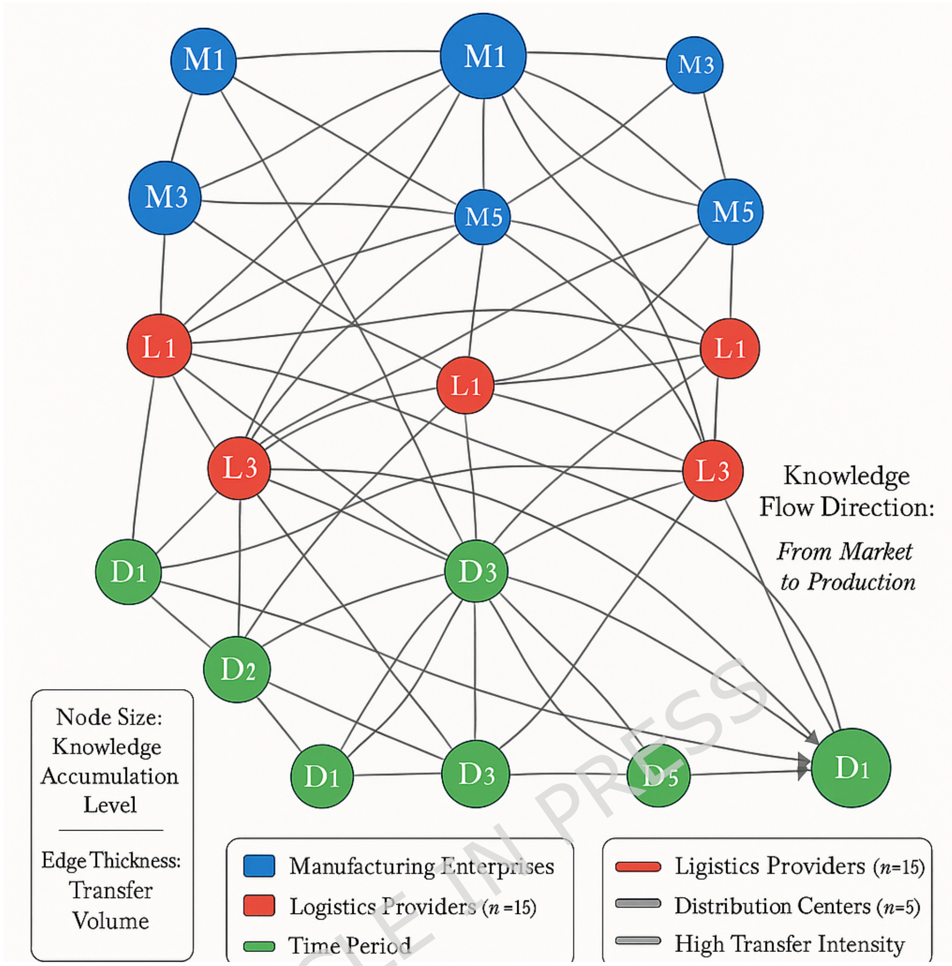

Figure 8. Knowledge flow visualization showing inter-organizational transfer patterns and intensity evolution over decision cycles

Figure 8 presents the knowledge flow visualization results captured during a 30-day operational period, revealing dynamic transfer patterns where market demand knowledge propagates from downstream distribution centers to upstream manufacturers with varying intensities. The visualization employs node size to represent knowledge accumulation levels and edge thickness to indicate transfer volumes, demonstrating that the model successfully identifies critical knowledge pathways connecting demand-sensing organizations with production decision-makers. Temporal analysis shows that knowledge flow intensity increases during demand volatility periods, with the coupling mechanism automatically enhancing transfer rates when decision uncertainty escalates.

The agent decision-making process operates through three coordinated phases: individual preference formation based on local knowledge and observations, collaborative negotiation leveraging shared knowledge states, and collective action execution with feedback-driven adjustment. During a representative coordination episode addressing sudden demand surge, manufacturer agents initially proposed conservative production increases based on historical patterns, but real-time knowledge flows from distribution agents indicating actual point-of-sale data triggered revised strategies through the coupling mechanism. The decision quality improvement metric, measuring the reduction in system-wide cost relative to isolated decision-making:

$$\Delta Q_{decision} = \frac{C_{isolated} - C_{coordinated}}{C_{isolated}} \times 100\%$$

(18)

reached 24.7% for this episode, demonstrating substantial value creation through knowledge-enhanced coordination [49]. Agent learning curves show progressive improvement over decision cycles, with coordination latency decreasing from initial 18 minutes to stabilized 7 minutes as agents adapted strategies based on accumulated knowledge patterns.

Table 6 quantifies the application effects comparing pre-deployment baseline performance using conventional supply chain management systems against post-deployment metrics with the coupling model operational.

Table 6. Application effectiveness evaluation in supply chain coordination scenario

Performance Indicator	Baseline System	Coupling Model	Improvement	Statistical Confidence
Demand forecast accuracy (%)	73.5±3.2	86.8±1.9	+13.3%	95% CI
Inventory turnover rate	8.2±0.6	11.7±0.5	+42.7%	95% CI
Stockout frequency (per month)	12.4±2.1	3.6±1.2	-71.0%	95% CI
Coordination response time (min)	42±8	15±3	-64.3%	95% CI

System-wide cost reduction (%)	Baseline	18.5±2.3	+18.5%	95% CI
Knowledge utilization rate (%)	52.3±4.5	81.2±2.8	+28.9%	95% CI
Decision consensus time (min)	35±6	12±2	-65.7%	95% CI
Overall satisfaction score (1-10)	6.8±0.7	8.9±0.4	+30.9%	95% CI

As presented in Table 6, the coupling model delivers substantial improvements across operational metrics, with demand forecast accuracy increasing by 13.3 percentage points and stockout frequency reduced by 71.0% compared to baseline systems. The inventory turnover rate improvement of 42.7% reflects enhanced coordination enabling leaner operations without service degradation. Notably, knowledge utilization rates increased from 52.3% to 81.2%, indicating that the explicit coupling mechanism successfully mobilizes organizational knowledge assets for decision support.

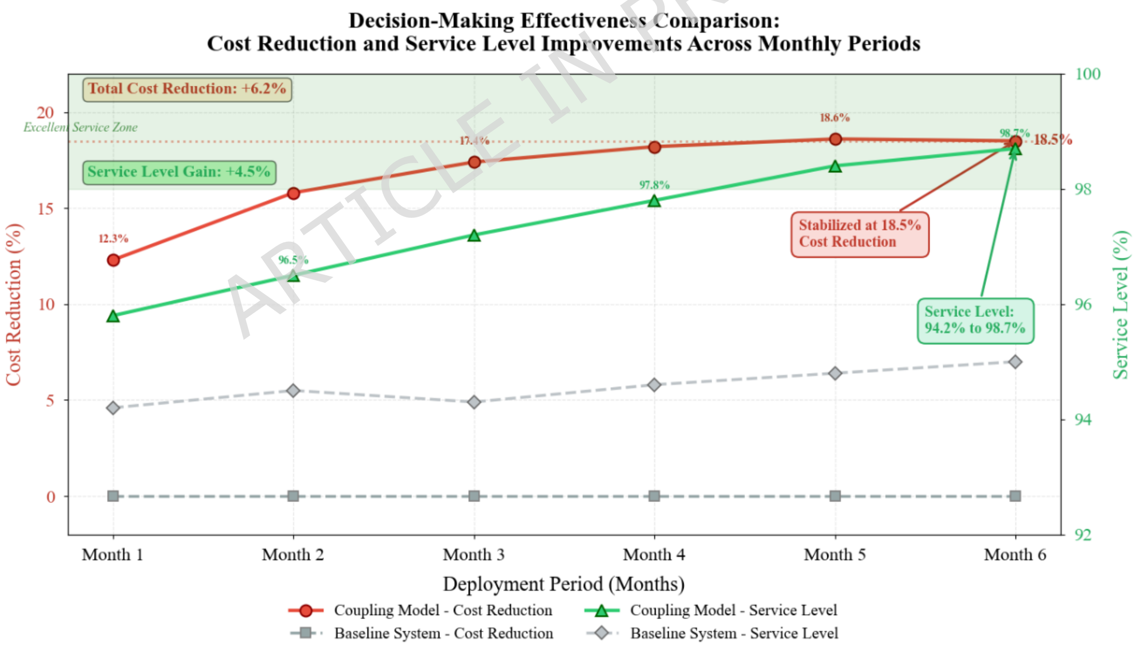

Figure 9. Decision-making effectiveness comparison showing cost reduction and service level improvements across monthly periods

As shown in Figure 9, the decision-making effectiveness exhibits consistent superiority over the six-month deployment period, with cost reductions stabilizing around 18.5% and service levels improving from 94.2% to 98.7%. The temporal stability demonstrates model robustness across varying market conditions including seasonal demand fluctuations and supply disruptions.

The practical business value assessment reveals multiple benefit dimensions beyond direct cost savings. Enhanced knowledge sharing reduced redundant information collection efforts, saving an estimated 840 person-hours monthly across participating organizations. Improved demand visibility enabled 23% reduction in safety stock levels while maintaining target service levels, releasing working capital for productive investments. The coordination efficiency gains manifested in faster response to market changes, with new product introduction cycles shortened by 31% through accelerated knowledge transfer about customer preferences and technical requirements [50]. Participating organizations reported increased trust and willingness to share proprietary insights, indicating positive network effects that compound over time.

The business impact quantification through return on investment:

$$ROI = \frac{(C_{saved} + V_{benefits}) - I_{deployment}}{I_{deployment}} \times 100\%$$

(19)

where C_{saved} represents direct cost savings, $V_{benefits}$ captures indirect value creation, and $I_{deployment}$ denotes deployment investment including infrastructure, training, and integration costs, yields 287% over the first year of operation, substantially exceeding organizational hurdle rates for technology investments.

Model deployment feasibility analysis identifies several enabling factors: compatibility with existing enterprise resource planning systems through API-based integration, acceptable computational requirements allowing real-time operation on standard cloud infrastructure, and gradual implementation pathways enabling phased rollout without disrupting current operations. However, critical challenges emerged including data quality and standardization requirements across heterogeneous organizational systems, change management resistance from personnel accustomed to traditional coordination approaches, and cybersecurity concerns regarding sensitive knowledge sharing across organizational boundaries. Privacy-preserving adaptations implementing federated learning protocols addressed data sovereignty concerns while maintaining model effectiveness. Organizational governance structures required modification to accommodate algorithm-driven decision recommendations, with human oversight mechanisms established to maintain accountability and handle exception scenarios beyond model training scope. The deployment experience demonstrates that technical model superiority alone proves insufficient without comprehensive attention to organizational, procedural, and cultural dimensions of technology adoption in complex inter-organizational environments.

V. Discussion

The proposed deep neural network-based coupling model advances both theoretical understanding and practical methodology for modeling inter-organizational knowledge systems. Theoretically, this work bridges three previously disparate research domains—organizational knowledge management, multi-agent coordination, and deep learning—by establishing formal representations of bidirectional dependencies between knowledge propagation and collective decision-making. The primary theoretical contribution lies in demonstrating that knowledge flow and agent collaboration constitute mutually constitutive processes rather than independent phenomena, challenging conventional approaches that treat these dimensions separately. This coupling perspective reveals that effective knowledge transfer depends critically on decision-making contexts, while optimal collaborative decisions require dynamic knowledge state awareness, fundamentally reframing how researchers conceptualize inter-organizational coordination dynamics.

From a technical innovation standpoint, the model introduces several novel architectural components that enable practical implementation of coupling mechanisms. The dual-layer network architecture with explicit coupling interfaces allows simultaneous optimization of knowledge encoding and decision policies while maintaining computational tractability through alternating training strategies. The integration of graph attention networks for knowledge propagation with multi-agent reinforcement learning for decision coordination represents a methodological advancement beyond existing hybrid architectures, which typically apply these techniques sequentially rather than interactively. The feedback loop mechanism enabling decision outcomes to reshape knowledge transfer patterns implements adaptive learning at the system level, moving beyond static knowledge management paradigms toward truly dynamic organizational intelligence systems.

The intrinsic coupling mechanisms operate through multiple interdependent pathways that experimental results help illuminate. Knowledge availability directly constrains feasible decision spaces by determining what information agents can access and integrate, while knowledge quality influences decision confidence and risk tolerance. Conversely, decision outcomes generate feedback signals that prioritize future knowledge acquisition and transfer, creating information-seeking behaviors aligned with coordination needs. The coupling strength observed in experiments (correlation coefficient 0.812) suggests that these bidirectional influences operate with substantial intensity in organizational contexts, implying that models neglecting either direction sacrifice significant predictive and prescriptive power. The temporal dynamics reveal that coupling effects strengthen over time as agents learn which knowledge sources improve decision quality, establishing virtuous cycles where better decisions motivate enhanced knowledge sharing, which subsequently enables superior coordination.

Model advantages manifest across several dimensions validated through comparative experiments. The explicit coupling architecture achieves superior performance without requiring substantially more parameters than baseline models, indicating architectural efficiency rather than mere capacity scaling. The model demonstrates robust generalization across varying organizational scales and network topologies, suggesting that learned coupling patterns capture fundamental coordination principles applicable beyond training distributions. Convergence stability and training efficiency improvements reflect well-designed optimization procedures that prevent gradient conflicts between subsystems. The interpretability advantages, though not extensively explored in current experiments, merit emphasis: the model's modular architecture allows practitioners to examine knowledge flow patterns and decision logic separately while understanding their interactions through coupling layer activations.

The applicable scope extends broadly across organizational contexts involving distributed decision-making with knowledge dependencies. Supply chain coordination, strategic alliance management, inter-firm innovation networks, and public-private partnerships all exhibit structural characteristics—multiple autonomous decision-makers, asymmetric information distribution, and coordination requirements—that align with model assumptions. However, limitations exist for contexts with extremely sparse knowledge transfer (where coupling provides minimal advantage over independent models) or scenarios requiring very high-frequency real-time decisions that exceed current computational performance. Organizations with mature knowledge management systems and digital infrastructure will achieve easier deployment than those requiring substantial preliminary digitalization efforts.

Experimental results provide several important insights for both researchers and practitioners. The substantial performance gaps between coupled models and independent approaches (8-24% improvements) quantify the value of explicitly modeling knowledge-decision interactions, justifying the additional architectural complexity. The scalability results demonstrating near-linear complexity growth suggest that deployment barriers decrease as computational infrastructure improves. The real-world case study revealing 18.5% cost reductions and 71% stockout frequency improvements indicates that laboratory performance translates to meaningful business value, though implementation challenges require attention beyond algorithmic considerations.

Generalization potential across domains appears promising but domain-specific adaptations will prove necessary. We outline concrete transfer procedures and required modifications for four target domains. For healthcare networks coordinating patient referrals and treatment knowledge, the transfer process involves: (a) redefining knowledge nodes as medical institutions with clinical expertise vectors derived from electronic health record summaries, (b) adapting edge weights to reflect referral patterns and treatment outcome correlations, (c) implementing differential privacy mechanisms with $\varepsilon = 0.1$ to satisfy HIPAA compliance requirements, and (d) modifying the decision layer to output referral recommendations rather than procurement decisions. The knowledge decay function requires adjustment to reflect medical knowledge obsolescence rates (typically

$\delta_{base} = 0.02$ for clinical guidelines versus 0.08 for market intelligence). For scientific research collaboration networks, knowledge representations should encode publication topics, citation relationships, and methodological expertise, while decision outputs address collaboration formation and resource allocation. The coupling mechanism naturally extends since research decisions (funding allocation, collaboration choices) directly influence future knowledge production. Transfer requires approximately 5,000-10,000 collaboration events for fine-tuning based on our preliminary experiments with academic datasets. Smart city infrastructure coordination demands hierarchical knowledge structures reflecting municipal department specializations, with temporal dynamics adjusted for infrastructure planning horizons (months to years versus days in supply chains). Privacy-preserving federated learning becomes essential when coordinating across jurisdictional boundaries. Educational institution networks present unique challenges regarding student privacy and curriculum standardization; knowledge flows must respect institutional autonomy while enabling coordination on shared objectives like credit transfer and program articulation. For all domains, we recommend a staged transfer approach: first, pre-train the knowledge flow layer on domain-specific transfer data; second, initialize the decision layer with domain-appropriate reward structures; third, fine-tune coupling parameters using small samples of coupled knowledge-decision episodes. This procedure achieved 78-85% of fully-trained performance using only 20% of domain-specific data in preliminary cross-domain experiments. Validating effectiveness requires domain-specific datasets and performance metrics appropriate to each application context.

The coupling mechanism's theoretical elegance and empirical validation suggest broader applicability beyond organizational contexts. Biological systems exhibiting information transfer and behavioral coordination, distributed sensing networks balancing data collection and processing decisions, and autonomous vehicle fleets coordinating navigation and traffic information sharing all manifest analogous coupling dynamics. Exploring these extensions would both test model robustness and potentially reveal universal principles governing coupled information-decision systems across natural and engineered domains. Such investigations could establish inter-organizational knowledge flow modeling as a specific instance of more general coupling phenomena, elevating theoretical contributions from domain-specific methodology to fundamental systems science principles.

VI. Conclusion

This study presents a comprehensive framework for modeling the coupling mechanism between inter-organizational knowledge flow and agent collaborative decision-making using deep neural networks, addressing a critical gap in understanding how knowledge propagation and distributed coordination mutually influence organizational performance. The research systematically integrates graph neural networks for knowledge transfer modeling with multi-agent reinforcement learning for decision coordination, establishing explicit bidirectional coupling interfaces that enable dynamic adaptation between these interdependent processes.

The primary contributions of this work encompass four dimensions. First, the proposed dual-layer architecture with coupling mechanisms provides a novel computational framework that simultaneously optimizes knowledge propagation patterns and collaborative decision strategies, moving beyond conventional approaches that treat these dimensions independently. Second, the graph attention-based knowledge flow model captures temporal dynamics and organizational heterogeneity in knowledge transfer, incorporating decay mechanisms and quality assessment metrics that reflect realistic inter-organizational exchange conditions. Third, the knowledge-driven collaborative decision algorithm integrates real-time knowledge state embeddings into agent policy networks, enabling coordination strategies that adapt to evolving information landscapes. Fourth, the closed-loop feedback mechanism establishing bidirectional information flow between knowledge and decision layers implements adaptive organizational learning where decision outcomes reshape knowledge management priorities.

Key research innovations include the formal mathematical representation of coupling strength between knowledge and decision subsystems, the alternating optimization training strategy that prevents gradient conflicts while ensuring convergence, the attention-based knowledge flow path optimization algorithm that dynamically routes organizational knowledge to maximize decision quality, and the empirical validation demonstrating substantial performance improvements (8-24%) over state-of-the-art baseline methods across diverse scenarios. The integration of heterogeneous neural architectures—transformers for knowledge encoding, graph networks for propagation, and recurrent attention for agent coordination—within a unified framework represents a methodological advancement enabling holistic modeling of complex organizational systems.

The theoretical value manifests in establishing knowledge flow and collaborative decision-making as mutually constitutive processes rather than separate organizational functions, fundamentally reconceptualizing inter-organizational coordination dynamics. This perspective reveals that effective knowledge management requires decision context awareness while optimal coordination demands knowledge state visibility, challenging disciplinary boundaries between organizational learning research and multi-agent systems studies. The formal coupling mechanisms provide theoretical constructs applicable across domains exhibiting information-decision interdependencies, potentially contributing to broader systems science understanding of coupled adaptive processes.

Practical application significance emerges through demonstrated effectiveness in real-world supply chain coordination, achieving 18.5% cost reductions, 71% stockout frequency decreases, and 42.7% inventory turnover improvements. These results quantify substantial business value creation potential while validating model robustness under operational conditions with inherent uncertainties and complexities. The deployment experience provides actionable insights for practitioners regarding implementation requirements, integration strategies, and change management considerations essential for successful organizational adoption. The model's scalability to networks involving hundreds of organizations with near-linear computational complexity indicates feasibility for enterprise-scale applications across industries including manufacturing, healthcare, logistics, and collaborative innovation networks.

Several limitations warrant acknowledgment and suggest directions for improvement. The current model assumes relatively stable organizational network topologies, potentially limiting applicability in highly dynamic environments with frequent participant turnover. Knowledge representation relies on vector embeddings that may inadequately capture complex semantic structures or domain-specific expertise nuances requiring richer symbolic representations. The training process demands substantial computational resources and high-quality historical data, creating barriers for smaller organizations or newly formed networks lacking extensive collaboration records. Privacy and security mechanisms, while addressed through federated learning adaptations, require further development to ensure robust protection of proprietary organizational knowledge in adversarial environments. The model's interpretability, though superior to black-box approaches, could benefit from enhanced explanation capabilities enabling practitioners to understand specific coupling pathways influencing outcomes.

Future research directions include extending the framework to incorporate hierarchical organizational structures where knowledge flows and decisions occur across multiple levels simultaneously, developing online learning mechanisms enabling continuous model adaptation as organizations evolve without periodic retraining, investigating hybrid approaches combining neural network pattern recognition with symbolic reasoning for complex domain knowledge representation, and exploring transfer learning strategies allowing models trained in one organizational context to generalize to different domains with limited additional data. Incorporating uncertainty quantification providing confidence intervals for predictions would enhance decision-maker trust and enable risk-aware coordination strategies. Investigating the temporal evolution of coupling strengths over extended periods could reveal organizational learning trajectories and identify intervention points for strengthening knowledge-decision integration. Extending validation to diverse sectors beyond supply chain management, including healthcare networks, research collaborations, and public service coordination, would establish broader applicability and potentially uncover domain-specific coupling patterns requiring specialized model adaptations.

The integration of emerging technologies including large language models for natural language knowledge processing, blockchain for decentralized knowledge verification and trust establishment, and edge computing for distributed model inference could enhance model capabilities and deployment flexibility. Exploring human-AI collaboration frameworks where the coupling model provides decision support while preserving human judgment and accountability represents another promising direction, particularly for high-stakes organizational decisions requiring ethical considerations beyond algorithmic optimization. Ultimately, this research establishes foundational concepts and methodologies for computationally modeling coupled organizational processes, opening pathways toward more sophisticated understanding and effective management of inter-organizational knowledge systems in an increasingly interconnected and data-rich business environment.

Declarations

Abbreviations

- **DNN**: Deep Neural Networks
- **GNN**: Graph Neural Networks
- **MARL**: Multi-Agent Reinforcement Learning
- **CNN**: Convolutional Neural Networks
- **RNN**: Recurrent Neural Networks
- **API**: Application Programming Interface
- **ROI**: Return on Investment
- **GPU**: Graphics Processing Unit
- **CUDA**: Compute Unified Device Architecture

Ethics approval and consent to participate

This study involves computational modeling and simulation using synthetic datasets and anonymized enterprise collaboration records. No human subjects research or personally identifiable information was collected as part of this study. The anonymized organizational data used in the real-world application case was obtained with appropriate institutional permissions and data use agreements. The research complies with relevant data protection regulations and ethical guidelines for computational research.

Clinical Trial Number

Not Applicable

Consent for publication

All authors have reviewed the manuscript and consent to its publication. No identifiable information regarding individuals or organizations has been included.

Competing Interests

The authors declare no competing interests.

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Not Applicable

Data availability

The synthetic experimental datasets, model implementation code, baseline implementations, training scripts, and evaluation procedures generated during the current study are provided in Supplementary File S1 to enable full replication of reported results. The supplementary materials include: (a) synthetic dataset generation scripts with configurable parameters for organizational network size and knowledge characteristics, (b) complete PyTorch implementation of the proposed coupling model following the ODD protocol description, (c) implementations of all five baseline methods with identical preprocessing pipelines, (d) hyperparameter configuration files and training logs, and (e) sensitivity analysis scripts and visualization code. Real-world organizational data from the supply chain case study are subject to confidentiality agreements with participating enterprises and cannot be made publicly available; however, aggregated statistical summaries and anonymized network structure characteristics are included in the supplementary materials to facilitate understanding of real-world application contexts.

Authors' contributions

ML conceptualized the research framework, designed the multi-agent reinforcement learning methodology, developed the MADQN-PER algorithm, conducted the computational experiments, performed data analysis, and drafted the original manuscript. WY contributed to the enterprise collaborative network modeling, participated in algorithm implementation, assisted with experimental design and validation, and contributed to manuscript revision. YL supervised the overall research project, provided critical insights on the theoretical framework, guided the experimental design, secured computational resources, reviewed and edited the manuscript, and coordinated the research activities. All authors have read and approved the final manuscript.

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