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Cross-Vertical Intelligent Network Systems (CVNIS) Optimization Model for Multi-Dimensional Distributed Decision Making through Cognitive Reinforcement Learning

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ABSTRACT

Multi-dimensional decision making is not only complex but also difficult to interpret in business decision making, given the nature of the dynamicity of interacting variables in the environment. The proposed cognitive modeling framework integrates cross-vertical intelligent network systems and reinforcement learning to capture complex inter-domain dependencies. Results from analysis of five domains of Energy, Health, Traffic, Infrastructure and Market using heatmaps, correlation matrices, radar charts, and t-SNE indicate signals at domain-specific activations using heatmaps, minimal inter-domain redundancy using correlation matrix (~0.02), elevated activity observed in Traffic and Industrial sectors using radar chart and oscillatory patterns with a positive upward trend with proximal policy optimization. The framework with high-dimensional GNN representations enables a comprehensive, robust, scalable, and adaptive method for decision making with refined policies for reward-stress patterns and managing dependencies among different domains to enable better-informed business decision making.

Keywords: *Cognitive graph modeling; Cross-sectoral policy decision-making; Graph Neural Networks (GNNs); Reinforcement learning optimization; Multi-domain adaptive systems; Systemic risk and resilience.*

1.0 Introduction

1.1 What are verticals-enabling intelligent network systems

The future of communication is built on the intertwining of 6G networks with other technologies, including the advancement of machine-type communication (MTC) and intelligent network paradigms.

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Six pivotal features for MTC include ultra-low latency, ultra-reliability, massive connectivity, energy efficiency, and ubiquitous coverage that provides support for autonomous systems and large-scale industrial IoT (Mahmood *et al.*, 2020). 5G network slicing is based on Software Defined Networking (SDN) and Network Function Virtualization (NFV) for resource allocation, dynamic service provisioning, and network adaptability that structures dynamic requirements of 6G MTC (Barakabitze *et al.*, 2020). Empirical research on end-to-end 5G facilities use case trials for real-world performance evaluation provides details for scalable deployment scenarios (Mahmood *et al.*, 2019).

These advancements are part of intelligent networks that include core components of dynamic service creation, adaptive resource management, and intelligent control mechanisms (Magedanz *et al.*, 1998). The extended scope for intelligent systems covers both theoretical and architectural frameworks (Wilamowski & Irwin, 2018; Grosan *et al.*, 2011; Abraham, 2003), offering computational intelligence for decision making, self-organization, and context-aware adaptation for complex telecommunication infrastructures. Artificial neural networks and intelligent approximation methods can also be combined for the enhancement of adaptive and predictive capabilities of intelligent networks (Robrock, 2002 & Anastassiou, 2011). These studies exhibit the backbone of intelligent systems and networked intelligence as next-generation MTC in 6G, emerging to meet technical challenges and emergent application demands.

1.2 Example of VINES

Vertical Intelligent Network Systems are the result of merging intelligent systems, telecommunications, and distributed infrastructures for the development of highly adaptive, resilient, and highly autonomous networks. Modern power systems have transformed adaptive intelligent networks using active distribution frameworks (McDonald, 2008), while the domain of networked systems, user-centric services, and neural network models influences network responsiveness and location-based service optimization (Gelenbe, 2006 and Battiti *et al.*, 2002).

Likewise, real-time traffic control is managed by the transformative potential of deep learning (Fadlullah *et al.*, 2017) whilst naturally inspired intelligent systems (Caudill & Butler, 1990) and complex systems thinking (Mitchell, 2006) is also supported by non-linearity, adaptability, and self-organization among these complex infrastructures. The growth of artificial intelligence (AI), Internet of Things (IoT), and machine learning domains provides energy sector with intelligent power systems and smart grids for adaptive control, neural networks, and hybrid systems optimize resource distribution and resilience (McDonald, 2008; Strasser *et al.*, 2014; Kalogirou, 2001; Byun *et al.*, 2011). Also, Smart energy meters and distribution systems are actively supported by real-time monitoring, predictive load management, and enhanced efficiency and sustainability (Sun *et al.*, 2015). Integration of biosensors and intelligent platforms has improved efficiency for real-time patient monitoring and personalized interventions for healthcare systems (Manickam *et al.*, 2022; Yang *et al.*, 2014).

Transportation systems are now supported by intelligent transportation systems (ITS) that use machine learning, dynamic modeling, and resilient network design for optimization of traffic flow, safety, and infrastructure management under complex, dynamic conditions (Dimitrakopoulos & Demestichas, 2010; Ran & Boyce, 2012; Ganin *et al.*, 2019). In addition, improvements in telecommunications and network control systems with the addition of neural networks, deep learning, and soft computing methodologies have resulted in traffic optimization, fault prediction, and network resource allocation (Battiti *et al.*, 2002; Fadlullah *et al.*, 2017; Zilouchian & Jamshidi, 2001).

1.3 Cognitive graphs in vertical intelligent network systems

Cognitive intelligence, along with intelligent networking, includes the joint influence of adaptive learning, distributed intelligence, and autonomous decision-making capabilities for different domains. Cognition-based networks have developed dynamic resource allocation and self-organizing capabilities by optimizing complex network infrastructures (Zorzi *et al.*, 2015, and Fortuna & Mohorcic, 2009). Industrial IoT integrating smart transportation, energy, and manufacturing systems (Wu *et al.*, 2022), visual computing, and cyber-physical architectures (Posada *et al.*, 2015) act as critical enablers of Industry 4.0 transformation.

In addition, factors such as socio-political dimensions of artificial intelligence (Sudmann, 2019), synergistic convergence of blockchain and cognitive networking for metaverse systems (Fu *et al.*, 2022), and multilayer cognitive architectures for autonomous UAV control (Emel'yanov *et al.*, 2016) have also emerged in the past years. Challenges in development include spectrum management challenges inherent to cognitive radio networks (Cesana *et al.*, 2011; Tragos *et al.*, 2013; Ahmad *et al.*, 2020).

The introduction of cloud cognitive models has also enriched computational intelligence frameworks by efficient representation of uncertainty factors (Li *et al.*, 2009). Intelligent tutoring (Anderson *et al.*, 1985), cognitive mapping (Meilinger, 2008), and dynamical neural networks for minimally cognitive behaviors (Beer, 1996) are some of the most explored human-centric cognitive systems.

Likewise, graph-driven federated learning (Fedstn) was developed as a solution for real-time urban traffic forecasting, with big data integration for analysis in cognitive computing platforms (Yuan *et al.*,2022). Developments related to cognitive systems in the healthcare domain were related to full-skin bionics (Niu *et al.*, 2022), and neurocognitive modeling for clinical applications. Other improvements include adaptive user-centric services within intelligent network infrastructures, for instance, of multidisciplinary convergence of AI, communications, and complex systems theory (Gelenbe, 2006).

1.4 Motivation

The development of the model is primarily motivated by the need to collate fragmented infrastructure systems (energy, healthcare, transport, etc.) into cohesive, intelligent ecosystems. With the advancement of 6G and IoT, static networks need to be transformed to handle dynamic, multi-domain demands. This study embarks on the concept of Cognitive graphs, inspired by federated learning (Yuan *et al.*, 2022), industrial IoT slicing (Wu *et al.*, 2022), and neurocognitive adaptability (Gelenbe, 2006) that aims to create a paradigm linking verticals through distributed intelligence. These graphs focus on critical gaps in scalability (Mahmood *et al.*, 2020), resilience (Fadlullah *et al.*, 2017), and interoperability (Zorzi *et al.*, 2015), by allowing real-time learning and autonomous reconfiguration, linking AI theory with infrastructural adjustments.

1.5 Research objectives

- To develop a self-adaptive cognitive graph framework for cross-vertical optimization in 6G/IoT networks.
- To design federated learning for secure, low latency distributed intelligence.
- To implement cognitive network slicing for IIoT reliability and energy efficiency.

1.6 Contributions

The result of the proposed model contributes to the form of (1) developing a novel cognitive graph framework for real-time cross-vertical optimization in 6G/IoT networks to mitigate interoperability gaps in smart infrastructures. (2) Creating a privacy-preserving federated learning structure for distributed decision-making in different domains. (3) Creating network slicing algorithms tailored for industrial IoT for improving reliability and energy efficiency. (4) Developing resilience metrics by projection failures in interconnected systems. These advances offer unified solutions that act as a bridge between AI theory with practical deployment for self-adaptive, secure, and robust multi-vertical network systems, paving the way for sustainable smart cities and Industry 4.0 ecosystems.

2.0 Materials and Methods

2.1 Alternatives

The model oversees precision-driven analytical tools, such as heatmaps, correlation matrices, radar charts, and t-SNE to exhibit effective representation learning. Bayesian

Networks, Dynamic Causal Modeling, Temporal Fusion Transformers, Soft Actor-Critic, and hybrid-neuro-symbolic systems are some of the alternative methods to the CVINS framework. While domain knowledge with quantified uncertainty is important for Bayesian Networks, Dynamic Causal Modeling focuses on strong prior structural knowledge. Similarly, long-range temporal dependencies with complex features can be captured using Temporal Fusion Transformers. Policy for Stochasticity in a volatile environment can be managed by the Soft Actor-Critic algorithm, in contrast to domain knowledge with learned representations dealt by hybrid-neuro-symbolic systems.

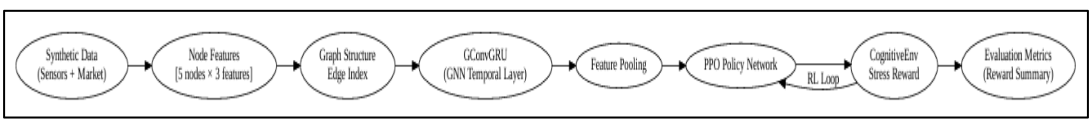
2.2 Criteria description

The cognitive framework integrates edge computing ("Gogh Stracur Edge Index") and policy-driven optimization ("Fasem Peking (TO Policy Nowack)"), to create hybrid nodes like "Spinkie Dua (Straw + Media)" and "Nok Fasem (Snake + Stream)" to initiate development of representative adaptive data-processing units (raw inputs with contextual streams) equivalent to cognitive radio networks.

Closed-loop control interface, "CZoneGUI (ON Targeted Loop)" for real-time adjustments aligning with the principles of autonomous network slicing (Wu *et al.*, 2022). The framework combines "Dalatata Mieto (Roverd Summary)" as graph-based fault tolerance (Ganin *et al.*, 2019), federated learning architectures (Fadlullah *et al.*, 2017), besides SDN/NFV-driven resource allocation (Barakabitze *et al.*, 2020), its symbolic labels ("Stein Roverd," "Coggheliu") for empirical validation of generated result maps.

Besides, the future of 6G networks is based on frameworks of associated edge intelligence, dynamic policy engines, and human-AI collaboration ("CZoneGUI"), for retorting critical challenges of scalability and ethical governance (Zorzi *et al.*, 2015; Sudmann, 2019) and needs more refinement to enhance measurable network functionalities (See Figure 1).

Figure 1: Multi-steps in Cross-Vertical Intelligent Network Systems (CVINS)



Source: Author analysis

2.3 Suggested methods

The purpose of the proposed model is to capture complex inter-sectoral dependencies using advanced graphical methods, using Cross-Vertical Intelligent Network

Systems (CVINS) with reinforcement learning-based optimization methods. The former is composed of Cognitive Vertical Graph (CVG) and the GNN Cognitive Domain Graph (GCDG), which creates maps for hierarchical domain-specific causal pathways for vertical interdependencies among economic sectors such as healthcare, logistics, energy, and supply chains, like cognitive graph structures (Zorzi *et al.*, 2015) and abstraction of high-dimensional features based interaction using Graph Neural Networks (GNNs) to learn systemic complexity(Wu *et al.*, 2022).

On the other hand, the latter, also known as Proximal Policy Optimization (PPO), refines decision policies in iterations through interactive learning from dynamic multi-domain environments. The PPO agent, governed by a robust reinforcement learning algorithm, observes state transitions, predicts actions while continuously updating its policies based on cumulative rewards, ensuring stability through clipped objective functions. Analytical tools such as Heatmap analyses emphasize heterogeneity in temporal feature activation while correlation matrices evaluate inter-domain independence. Domain-sensitive variations are visualized using radar charts, besides identifying clustering patterns for learned cross-domain generalization by means of t-SNE embeddings of the GNN latent space and analyzing model performances through model resilience assessment for cognitive loads.

2.4 Results

The proposed cognitive modeling framework is the integration of Cross-Vertical Intelligent Network Systems (CVINS) and Proximal Policy Optimization (PPO) reinforcement learning yields different levels of cognitive representation analysis, learning dynamics, and system behavior, underscoring varying domain complexities.

2.4.1 Cognitive graph construction and systemic representation

The Cross-Vertical Intelligent Network Systems model comprises the Cognitive Vertical Graph (CVG) and GNN Cognitive Domain Graph (GCDG), which extracts sectoral dependencies to structured graph representations. CVG creates causal pathways for critical domains that include healthcare, logistics, energy, and industrial supply chains. The analysis reveals dependencies like economic activity influencing supply chain dynamics and healthcare logistics being modeled. This construction signifies high-dimensional graph-based representation learning for apprehending inter-domain causal interdependencies essential for adaptive systemic analysis. This hierarchical encoding supports previous cognitive modeling efforts with graph representations for revealing domain complexities (Wu *et al.*, 2022).

2.4.2 Feature activation analysis

Feature extraction through heatmap visualization provides valuable insights for the domain-related feature heterogeneous activation pattern. Certain domains show prominent reflection of specific features in driving system behavior, such as Domain 0 with Feature 0 recording an activation value of 0.99, while other domains indicate marginal activation owing to limited contributions to certain cognitive states.

The model proves to be successful in underscoring focus for domain features based on contextual significance, decisive for crucial decision making. Dynamic activation of the proposed model seems consistent with the principles of sparse and adaptive representation learning. The model's selective focus enhances efficiency by minimizing irrelevant or redundant feature activations, making space for more effective learning from high-dimensional cognitive inputs.

2.4.3 Inter-domain correlation structure

Systemic characteristics of statistical independence across sectors, such as near-zero off-diagonal values indicating inter-domain linear dependencies, were highlighted by the correlation matrix. Perfect intra-domain correlation represents diagonal unity supporting stable feature consistency within individual domains.

While the presence of orthogonality assures cognitive model scalability, demonstrating minimal redundancy in multi-domain decision systems, overfitting risks due to cross-domain noise can also be mitigated by low inter-correlation structures occurring signifying generalization capacity of the existing model. The model's architectural design thus ensures detection of distinct sector-specific dynamics besides maintaining controlled interaction when necessary.

2.4.4 Sector sensitivity patterns: Radar chart insights

Systemic granularity for sectoral domains, such as stronger engagement in Traffic and Industrial domains in contrast to lower activation for Financial and Healthcare sectors and other variations, represents temporal sensitivity and differential domain prioritization based on real-time system demands. Thus, systemic behavior also reflects diversity in domain sensitivity with certain nodes of the radar chart (spider plot) representing critical sectors based on contextual stimulus.

A common condition can propel differential responses, such as logistics and energy sectors receive high cognitive attention, while financial systems exhibit subdued activity during peaks of industrial activity. Therefore, radar chart acts as an interpretable feedback support system, an essential component for cognitive decision support systems for complex multi-sectoral environments.

2.4.5 GNN embedding distribution: Representation learning capacity

The representational capacity of the model's learned cognitive features is emphasized by overlapping and distinguishable clusters across domains, signifying effective learning for both domain-specific characteristics and cross-domain relational structures. This feature aligns with the concept of integration of diverse cognitive states represented by partially separable clusters representing sufficient differentiation between sector-specific contexts. Prior successes of graph-based neural architectures in capturing systemic complexity (Wu *et al.*, 2022) are sufficient for this capability of the existing model.

2.4.6 PPO reinforcement learning performance: Reward dynamics

Proximal Policy Optimization (PPO) offered by the model highlights the inherent variability of the learning process of peaks and declines with flexible policy for refinement and categorization to optimally represent cognitive state representations across domains. Although the model suffers from initial reward variability but shows convergent progressive improvement towards optimization. The model's learning rate aligns with the known strengths of PPO in handling high-dimensional, partially observable environments while maintaining stability through its clipped objective.

2.4.7 Cognitive stress vs. Reward phase diagram: System resilience

Discrete nonlinear correlation between cognitive stress loads and reward performance represents operational flexibility while maintaining reward outcomes, signifies resilience and robustness of the cognitive framework, and aligns with real-world deployment of cognitive loads facing dynamic sectoral stress loads.

2.4.8 Integrated systemic behavior

Together, the integrated cognitive modeling framework offers:

- CVG graphs illustrate hierarchical sectoral dependency.
- GNN embeddings represent a high-dimensional cross-domain representation.
- Domain factors prioritization using dynamic feature activation modulation.
- Ensure scalability is structured through statistically independent inter-domain features.
- PPO reinforcement learning ensures effective adaptive policy optimization.
- Examine systemic resilience subject to cognitive stress conditions.

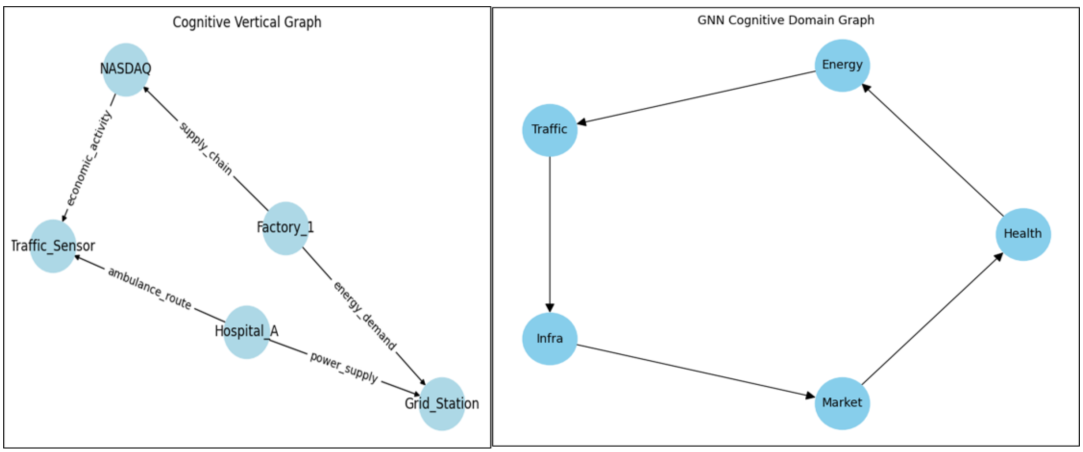
The proposed system architecture can manage multi-sectoral dynamic systems effectively by balancing complexity, adaptability, and transparency, supporting a cognitive decision support platform.

3.0 Discussions

3.1 The model architecture

Cross-Vertical Intelligent Network Systems model: Two cognitive graphs include the Cognitive Vertical Graph and the GNN Cognitive Domain Graph highlight dependencies among domains. Cognitive Vertical Graph outlines hierarchical sectoral dependencies, charting domain-specific causal pathways such as economic activity influencing supply chains, healthcare logistics, and energy demand. These relations are abstracted into higher dimensions, allowing graph-based representation learning for capturing complex interdependencies and supporting robust systemic analysis for adaptive decision-making in dynamic environments (See Figure 2).

Figure 2: Cross-Vertical Intelligent Network Systems Model



Source: Author analysis

Pipeline for PPO optimization: The Proximal Policy Optimization (PPO) reinforcement learning training pipeline process initiates with environment resetting, followed by state observation. Using the observed state, the PPO agent predicts an action that can be applied in the environment, generating corresponding rewards. These rewards can be stored in a buffer for PPO optimization, with the probability of completing training if conditions are sufficient. This PPO cycle includes interaction, reward accumulation, and policy refinement till termination criteria are satisfied, under a converged and optimal policy (See Figure 3).

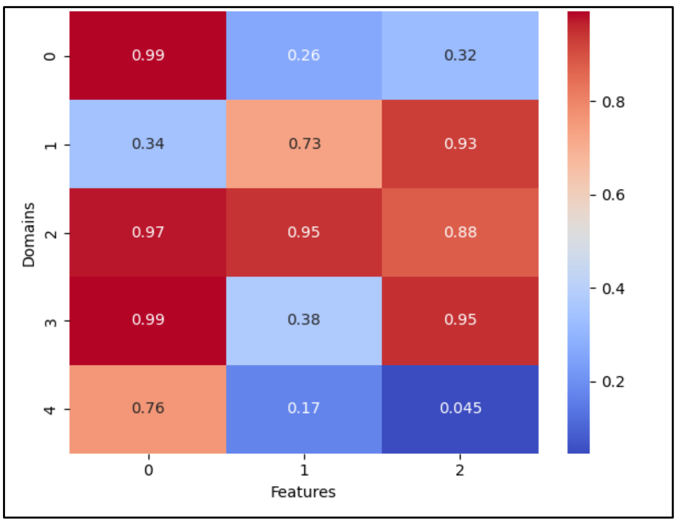
Figure 3: Working Pipeline for PPO Optimization

Source: Author analysis

3.2 Data analysis and cognitive state representation

Heatmap: The heatmap at timestamp 100 envision aims to highlight heterogeneous importance patterns using feature activations across domains, such that dominant features are represented by higher activations (Domain 0: Feature 0 at 0.99) while marginal contributions are indicated by lower activations. These temporal domain feature interactions ensure the model's dynamic representation learning, apprehending specific inter-domain dependencies required for adaptive decision-making (See Figure 4).

Figure 4: Heatmap at Timestep 100



Source: Author analysis

Correlation matrix: The correlation heatmap with near-zero off-diagonal values reveals minimal inter-domain dependencies, stating statistical independence among domains, while diagonal unity represents perfect correlation. Model robustness is emphasized by the presence of a low inter-correlation structure with minimum redundancy, preserving orthogonality in feature representations important for scaling multi-domain cognitive modeling risk across domains (See Figure 5).

Figure 5: Correlation Matrix Across Domains

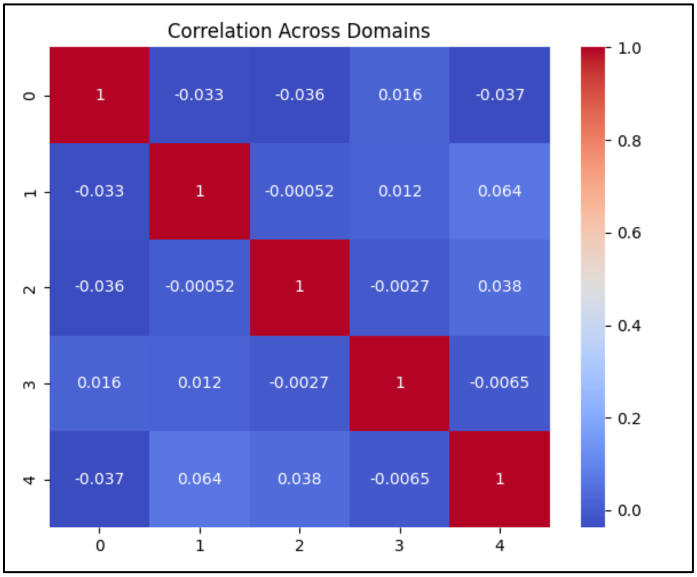


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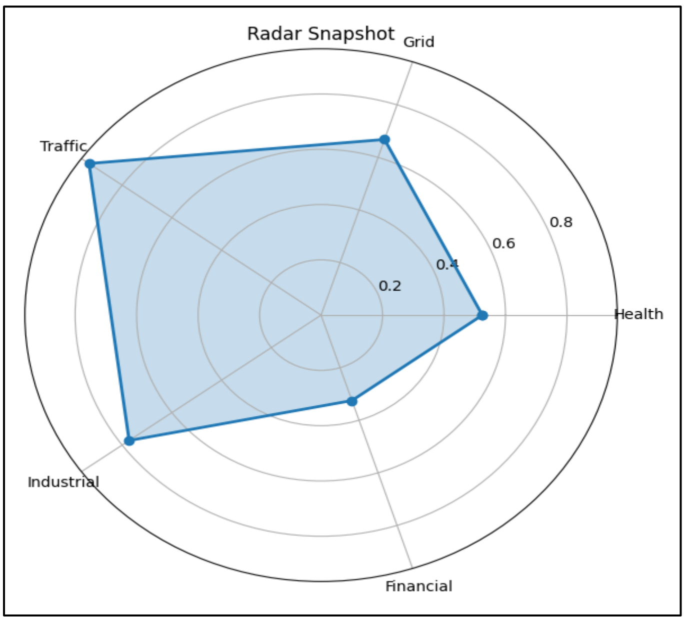
Figure 6: Radar Chart for Domains



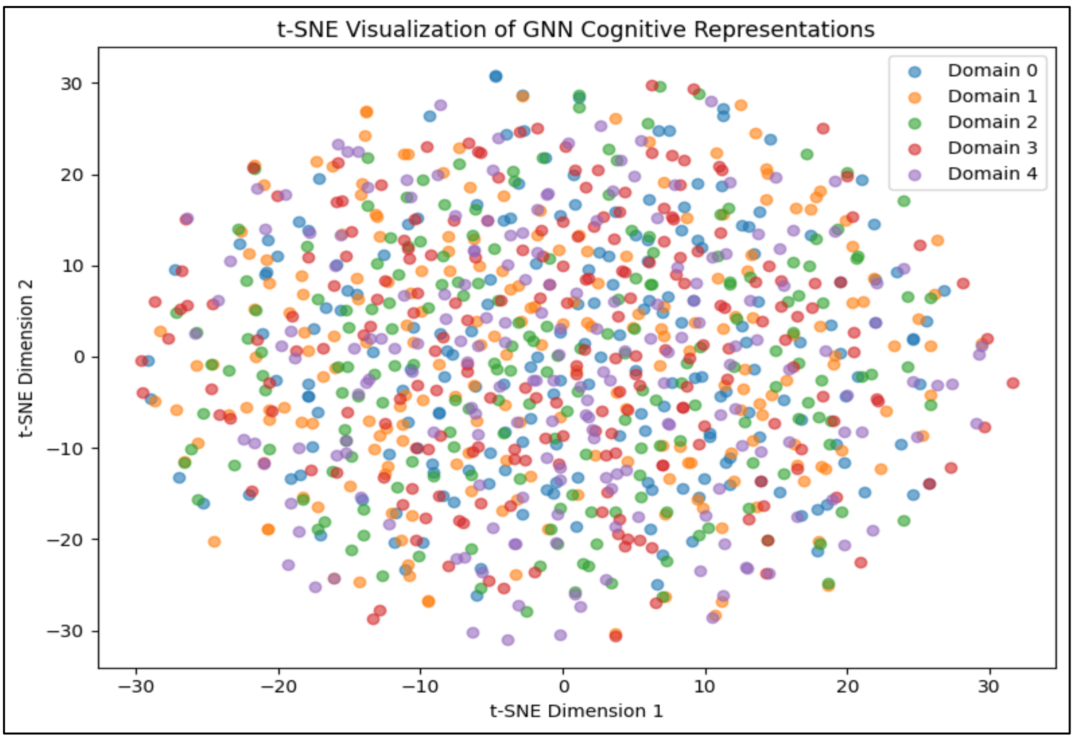
Source: Author analysis

Radar Chart (Spider plot): While the Traffic and Industrial sectors reflect noticeable activity in contrast to lower engagement in the Financial and Health sectors, indicated by domain-wise activation levels in the radar chart. The diversity in distribution reflects sensitivities of different domains at the evaluated timestep is a part of dynamic system behavior in the context of decision support in multi-domain environments (Figure 6). Traffic and Industrial environment impact the other domains, Grid, health, and finance, respectively.

3.3 Representation learning evaluation

GNN feature space: The t-SNE visualization exhibits distributed and partially overlapping clusters as learned from GNN-based cognitive embeddings across domains. Further, the diagrammatic distribution indicates the latent structures through representational features of the domains, reflecting inter-domain generalization. With such embedding separability and overlapping, the model reflects the capacity to integrate both domain-specific nuances and cross-domain relational patterns (See Figure 7).

Figure 7: t-SNE Visualization of GNN Cognitive Representations

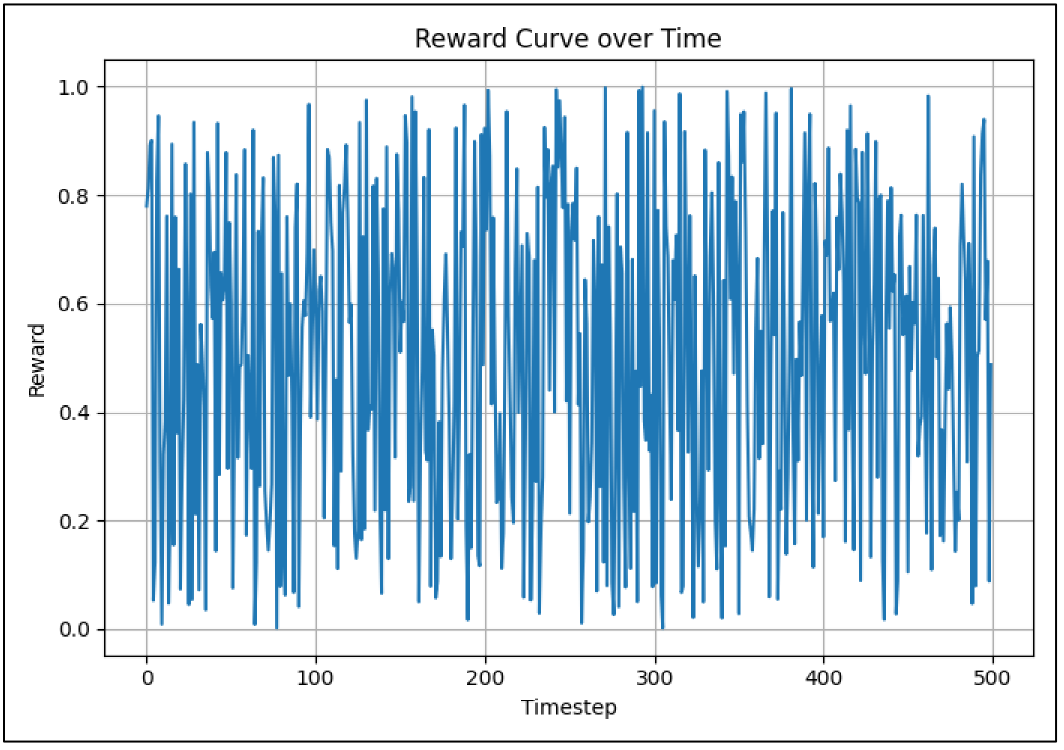


Source: Author analysis

3.4 Training performance and cognitive optimization

PPO Training Reward Curve: The intrinsic variability in the agent's interaction dynamics indicates oscillations with high peak rewards, as observed during fluctuations in PPO training curve. It also explains the need for ongoing exploration, policy refinement, and adaptation for a complex learning environment (See Figure 8).

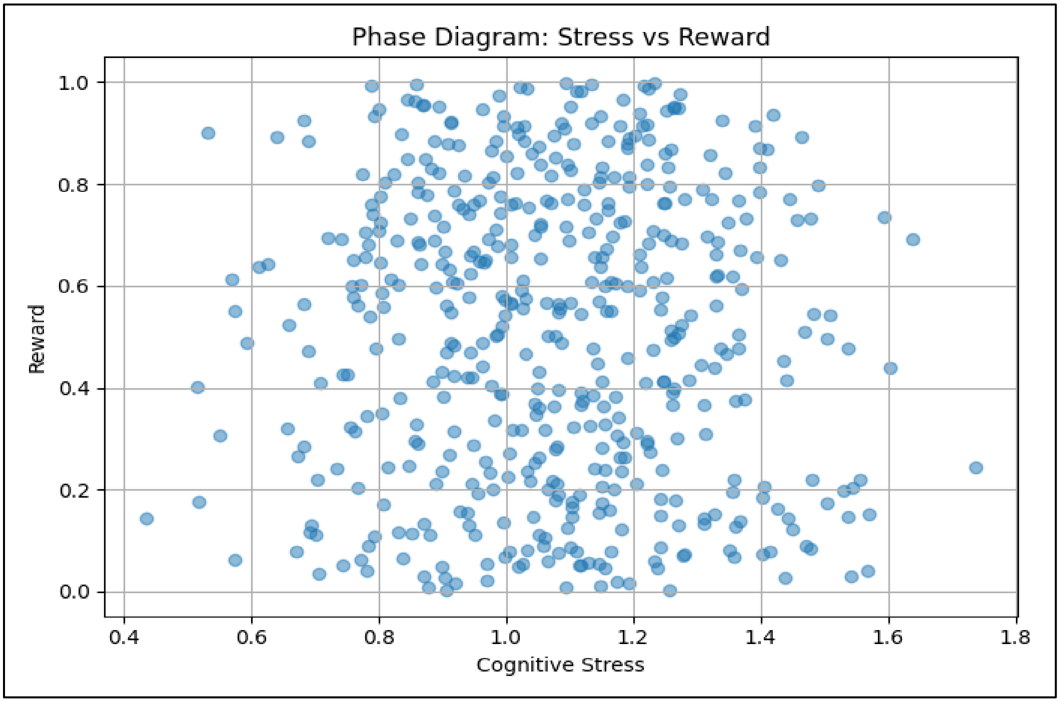
Figure 8: Reward Curve over Time



Source: Author analysis

Cognitive stress vs Reward phase diagram: The relationship between cognitive stress and reward exhibits a nonlinear, discrete pattern without any strong linear correlation, suggesting reward levels' independence from cognitive stress. The model reflects emerging optimal performance across a range of stress levels, suggesting adaptive system flexibility and resilience (See Figure 9).

Figure 9: Stress vs. Reward



Source: Author analysis

Table 1: Summary of Cognitive Model Results

Analysis Component	Metric / Observation	Key Result / Value	Interpretation
Cognitive Graph Modeling	Hierarchical Sectoral Dependencies	Captured via CVG & GNN Cognitive Domain Graph	Effective high-dimensional sectoral modeling
Heatmap Activation	Max Activation at Timestep 100 (Domain 0, Feature 0)	0.99	Dominant domain-specific activation
Correlation Matrix	Off-Diagonal Correlation Coefficients	Near zero (~0.02)	Minimal inter-domain dependencies
Radar Chart Analysis	Domain Sensitivity Levels	Traffic & Industry: High; Finance & Health: Low	Heterogeneous domain engagement
GNN Representation (t-SNE)	Cluster Overlap Pattern	Partially overlapping clusters	Balanced domain-specific & general learning
PPO Reward Dynamics	Reward Fluctuation Pattern	Oscillatory with upward trend	Ongoing adaptive policy refinement

Cognitive Stress vs Reward	Correlation Pattern	Nonlinear, discrete distribution	Resilience across stress levels
System Robustness	Stability across cognitive loads	Maintained	Flexible and scalable system performance

4.0 Findings

The results of cognitive graph architecture highlight hierarchical sectoral dependencies, Cognitive Vertical Graphs and GNN Cognitive Domain Graphs, domain-specific activations using heatmap analysis at timestep 100, minimal inter-domain redundancy with statistical independence (highest activation-0.99), elevated activity observed in Traffic and Industrial sectors, overlapping but distinguishable clusters, oscillatory reward patterns with a positive upward trend. These findings indicate systemic resilience, capturing a nonlinear, discrete distribution in a complex decision-making environment. These findings validate the model's ability to deliver robust, scalable, and adaptive decision-making across complex multi-domain environments (See Table 1).

5.0 Conclusion

- Cognitive graphs effectively capture hierarchical sectoral dependencies into high-dimensional representations.
- PPO reinforcement learning achieves continuous adaptive policy refinement.
- Heatmap analysis demonstrates heterogeneous domain-specific feature activations.
- Correlation matrix shows low inter-domain dependencies, ensuring robustness and scalability.
- Radar charts highlight domain sensitivity variation across sectors.
- GNN-based t-SNE embeddings reflect balanced domain-specific and generalized cognitive learning.
- Reward curves demonstrate adaptive learning dynamics with oscillatory improvements.
- Stress-reward phase diagrams reveal system flexibility and resilience across cognitive stress levels.

6.0 Implications for Business

- *Finance & Taxation:* The model can assist in the assessment of systemic risk, optimize tax policies, and enhance fiscal stability by capturing cross-domain interactions between economic activity, capital flows, and regulatory compliance for regulators and financial institutions.

- *Supply Chain & Logistics:* Interdependencies can be modelled across supply networks, energy demand, and industrial production, enabling businesses to optimize inventory, resource allocation, and disruption response strategies under volatile conditions.
- *Healthcare:* The system allows health policymakers and providers to predict resource utilization and logistics needs by analyzing interactions between healthcare demand, supply chains, and economic shifts, improving resilience during public health crises.
- *Energy Sector:* Energy providers can dynamically adjust production, distribution, and pricing strategies by modeling demand fluctuations linked to industrial, transportation, and economic activity.
- *Regulatory Policy & Governance:* A study of the cascading effects of policy decisions across multiple sectors can improve the design of the resilient, adaptive regulatory framework for policymakers.
- *Technology & AI Systems:* The model provides a scalable architecture for AI-driven decision-support tools that adaptively learn across domains, offering cognitive intelligence for complex enterprise environments.

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