SEGN: A Philosophy-Driven Framework for Condition-Dependent AI Reasoning

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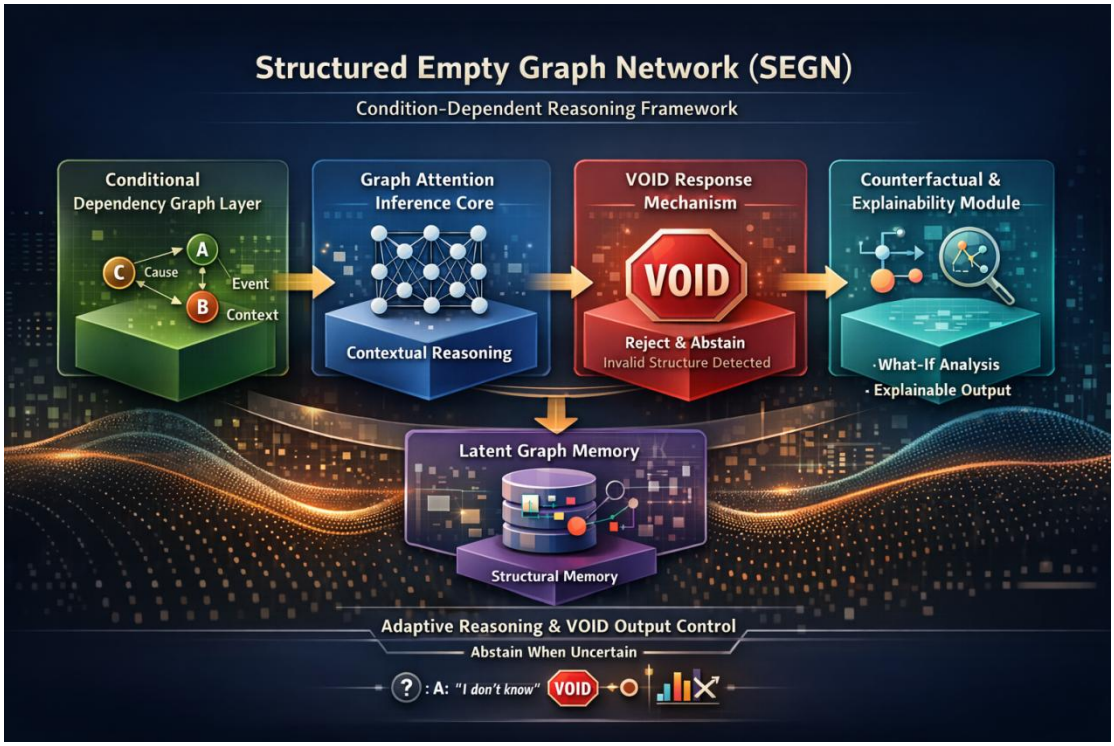

Architecture of the Structured Empty Graph Network (SEGN)

This diagram illustrates the end-to-end architecture of the Structured Empty Graph Network (SEGN), a condition-dependent reasoning framework designed to prevent unsupported inference under structural uncertainty. SEGN operates through five tightly coupled modules: (1) a Conditional Dependency Graph Layer that formalises causal and contextual prerequisites; (2) a Graph Attention Inference Core that performs structure-aware reasoning; (3) a VOID Response Mechanism that explicitly rejects inference when structural closure is violated; (4) a Latent Graph Memory that preserves incomplete or previously invalidated structures for future repair; and (5) a Counterfactual and Explainability Module that provides interpretable "what-if" analysis. Together, these components enable SEGN to replace hallucination-prone completion with principled abstention, repair, or explainable output, supporting reliable reasoning in high-uncertainty environments.

Abstract

In this study, the author proposes a non-essentialist structural inference modeling approach to address the limitations of traditional graph neural networks (GNNs), such as weak inference ability and insufficient interpretability, especially under missing conditions, structural perturbations, and ontological rigidity. A Structural Emptiness Graph Network (SEGN) is constructed based on the ontology reversal principle that "entities emerge with conditions." The model introduces a null response mechanism, counterfactual inference module, chain repair strategy, and latent graph memory unit to form a dynamic causal inference pathway that is rejectable, repairable, and traceable. In experiments on multi-agent path prediction and structurally incomplete graphs, SEGN achieves a 78.4% reasoning recovery rate under 30% structural perturbation, a 0.24 improvement in the XAI explanatory index, and a 15.8% reduction in the standard deviation of structural stability, significantly outperforming baseline models such as GCN and GAT. These results confirm that the structural philosophy of "emptiness and conditional manifestation" can be formally embedded into AI systems, offering a feasible interdisciplinary pathway toward building next-generation reasoning models with structural adaptability, causal transparency, and ethical rejection capabilities.

Keywords: ontology reversal, sex-space reasoning, graph neural networks, conditionally dependent intelligences, philosophy of computation

I. Introduction

Graph Neural Networks (GNN) have become an important method for modeling structured data and performing multi-hop reasoning, and are widely used in knowledge graphs, path planning and recommender systems. However, existing GNNs generally rely on static ontology settings and fixed structural paths, which are difficult to adapt to structural perturbations, missing conditions, and semantic interruptions in real-world environments. This "ontology-fixed-structure-rigid" modeling paradigm limits the robustness and causal transparency of AI systems in complex dynamic scenarios.

In order to solve the above problems, this paper proposes Structural Emptiness Graph Network (SEGN), which is the first time to formalize the idea of śūnyatā in Buddhist philosophy into a structure-driven AI modeling mechanism. SEGN introduces the path of "ontological inversion", i.e., the existence of entities is no longer taken as a preset input, but is dynamically activated through the aggregation of structural conditions in the graph, which is formalized as the mechanism of "Conditional Triggered Ontology Generation". mechanism. The framework integrates three core modules: (1) Void Response, which is used to recognize structural breaks and reject untenable reasoning; (2) Latent Graph Memory, which is used to awaken missing paths with the help of historical structural fumigation and assist chain repair; (3) Counterfactual Simulation; and (4) Counterfactual Simulation, which is used to recognize structural breaks and reject untenable reasoning. Counterfactual Simulation), which is used to verify key causal nodes and generate causal interpretable paths.

This paper focuses on two core research questions: (1) How to construct a graph neural inference model with path perception, self-repair and rejection in a graph environment with structural perturbation and condition shedding? (2) How to translate the philosophical logic of "causal manifestation and non-essential existence" into a formally realizable structural reasoning framework?

The contributions of this paper are as follows:

1.constructing SEGN framework and ontology reversal mechanism: proposing an ontology modeling paradigm with "structural manifestation" as the core, mapping the philosophy of sex and emptiness into a structural triggering mechanism, which is different from the dynamical graph GNN that only models the side evolution paths and emphasizes that entities are activated by the structure instead of being predetermined;

2. design rejection response and structure smudging mechanism: integrate Void rejection labeling, graph memory and chain repair process to form a set of graph reasoning path generation system with structural adaptability and causal self-interpretation capability;

3. systematically verify the performance of SEGN under complex graph perturbation: under 30% structural defect condition, SEGN realizes 78.4% inference recovery rate, XAI explanation index improves by 0.24, and structural stability variance decreases by 15.8%, which is significantly better than the mainstream models such as GCN and GAT in terms of both performance and interpretability.

In summary, SEGN is not only a graphical neural structure inference framework, but also a philosophical reconstruction of AI ontology modeling paradigm. By embedding structural philosophy into the design of modeling mechanism, SEGN demonstrates how AI systems can have the structure-aware capability of “rejectable, repairable, and explainable”, and provides reproducible engineering paths and theoretical support for the construction of trustworthy reasoning intelligences under high uncertainty environments.

II. Related Research

This chapter is divided into two directions: one is to explore the theoretical foundations of philosophy-driven structural modeling, and the other is to review the evolution of graphical neural network techniques for structural reasoning and adaptive modeling. Each section concludes with "How this research differs from existing work" to clearly position the unique contribution of this thesis.

2.1 Philosophy-Driven Structural Revealing and Non-Essential Modeling Paths

The Buddhist philosophy of śūnyatā asserts that all phenomena have no inherent essence, but are dependent on the aggregation of karmic conditions for their manifestation (Garfield, 1995). This non-essentialist idea has been further developed by Vaisnavism into the theory of "three natures", including ubiquity (subjective misinterpretation), etativity (conditional manifestation), and reality (structural rationality) (Beinorius, 2000), which provides philosophical analogies for bias modeling, conditional logic, and structural feasibility in artificial intelligence. Analogy.

"The concept of ālaya-vijñāna, on the other hand, provides the philosophical basis for mapping subconscious memories, describing how traces of experience (vāsanā) and seeds of causation (bīja) surface under the activation of specific structural conditions (Stanford Encyclopedia of Philosophy, 2024). Accordingly, this paper constructs a Latent Graph Memory (LGM) mechanism to realize path repair and counterfactual generation in structural break scenarios.

In recent years, scholars have tried to introduce philosophical ideas into AI modeling, for example, Zhou et al. (2022) proposed a decentralized collaborative mechanism based on the Taoist concept of "Wu Wei", and Tian et al. (2023) explored a model for correcting reasoning under the perspective of cognitive bias. However, no study has formalized the Buddhist philosophy of nullity into a graph neural network structural mechanism.

The difference between the present study and the existing work is that we are the first to engineer the idea of "emptiness" into a mechanism of "structural triggering - ontological manifestation", and propose a path of ontological reversal, which realizes the non-preconceived

manifestation of entities and the causal recovery driven by structural logic. The path of ontology reversal is proposed to realize the non-preset appearance of entities and the causal recovery driven by structural logic.

2.2 Structural Rigidity and Modeling Evolution in Graph Neural Networks (GNN)

Graph Neural Networks (GNN) are widely used in non-Euclidean structural modeling, and their basic structure includes message passing, neighbor aggregation and state update (Scarselli et al., 2009). Representative models such as GCN (Kipf & Welling, 2017), GAT (Veličković et al., 2018), and GRN (Li et al., 2016) excel in social networks, knowledge graphs, and structured question-answering tasks.GNNs have also been extended to causal graphical reasoning (Zhang et al., 2020), program induction (Allamanis et al., 2018) and heterogeneous graph relationship modeling (Schlichtkrull et al., 2018).

However, mainstream GNNs generally adopt the ontology modeling assumption of "entity prior-structure solidification" (Davis et al., 1993; Smith & Welty, 2001), which lacks the ability to cope with structural perturbations, conditional missing and semantic disruption scenarios. Dynamic graph neural networks (Kazemi et al., 2020) achieve partial adaptation by modeling structural evolution, and graph contrast learning methods (You et al., 2021) attempt to improve model robustness. However, these methods have not yet broken through the ontology-locked logic of "predefined entities", and it is difficult to realize the reasoning path of structure first and entity later.

As for the philosophical path, academics have proposed the theories of "ontological diversity" (Hawley, 2019) and "meta-ontological structure" (Krzanowski & Polak, 2022) to break the ontological monism, and advocate that the model should have the ability of structural reconstruction. structural reconfiguration capabilities. However, most of the existing studies remain at the conceptual level and lack formal realization and evaluation in GNN structures.

The key difference of this study is that our proposed SEGN model is based on the concept of "ontology reversal", which does not presuppose entities, but takes structural conditions as the reasoning trigger premise, and embeds a rejection output mechanism and a mapping memory path

repair capability, which breaks through the bottleneck of structural adaptation fundamentally.

III. Modeling

3.1 Modeling Overview

In order to more clearly demonstrate the modeling philosophy and mechanism differences in this study, Figure 1 compares the core modeling paths of traditional Ontology-Prior GNNs and the Structure-Triggered SEGN proposed in this paper.

In traditional graph neural networks, models commonly rely on predefined entities (e.g., node categories, attribute labels) and fixed path structures for information propagation and inference. Such approaches assume that the ontology is revealed before the structure, ignoring the inference uncertainty caused by missing conditions, structural perturbations and broken paths in real graph environments.

In contrast, SEGN follows a philosophical modeling logic of "structure first, entity emergence", and proposes Ontological Inversion: entities are activated and participate in reasoning only when the structural relationships in the graph satisfy certain conditions. On this basis, SEGN introduces three key modules: (1) VOID Response Mechanism, which rejects the inference output when the structure is incomplete; (2) Latent Graph Memory (LGM), which is used to reconstruct the causal chain; and (3) Counterfactual Repair Mechanism, which realizes the path closure and maintenance of structural consistency.

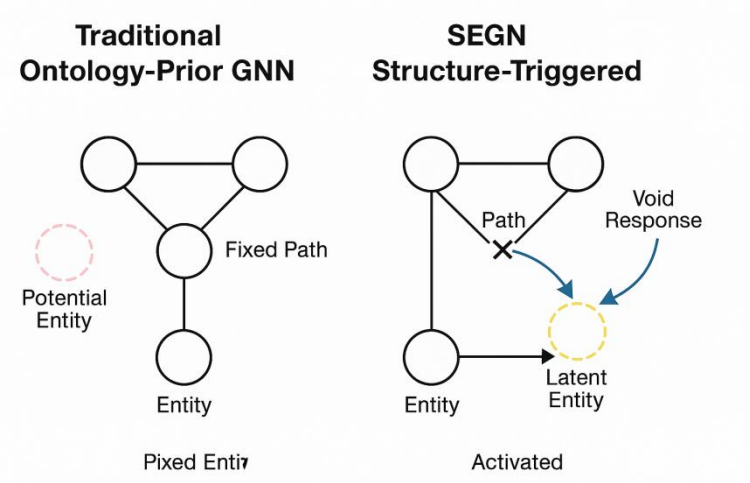

Figure 1. Comparison between Traditional Ontology-Prior GNNs and Structure-Triggered SEGN

SEGN is driven by the input structure graph, and after recognizing the structure state, it can automatically enter the "reject-repair-explain" reasoning process, realizing an AI intelligence

reasoning paradigm with structure perceptibility, path self-repair, and reasoning interpretability. This two-way philosophy-engineering design not only overcomes the modeling vulnerability of traditional GNNs in dynamic environments, but also provides a paradigm innovation for credible reasoning in structurally incomplete scenarios.

Table 1.Mapping table of philosophical concepts to modeling mechanisms

Philosophical Concept	English Term	CorrespondingModeling Mechanism
Emptiness (śūnyatā)	Emptiness	VOID State Rejection Mechanism
Ontological Non-Presupposition / Conditional Manifestation	Ontological Inversion	Node Structure Trigger Judgment Function
Storehouse Consciousness (ālaya-vijñāna)	Latent Graph Memory	Latent Graph Memory and Karmic Trace Activation
Causal Structure and Conditional Reorganization	Causal Conditioning	Counterfactual Path Construction and Structural Repair Module
Dependent Origination without Voidness / Causal Transparency	Causal Traceability	Significant Path Explainability Generation

3.2 SEGN System Structure and Philosophical Modeling Framework

3.2.1 Non-essentialist philosophical motivation and structural reasoning starting point

Traditional graph neural networks generally follow the “entity presupposition” paradigm, i.e., defaulting to all nodes being manifest at the initialization stage of the graph and serving as the starting point for information propagation. This type of modeling works well in static structures, but is prone to semantic drift, path failure, and uninterpretable reasoning when facing broken paths, incomplete conditions, or evolving graph structures.

In order to break through this bottleneck, SEGN (Structural Emptiness Graph Network) proposes to construct a structure-driven non-essentialist graph intelligence framework based on the modeling principles of Buddhism's “karmic emptiness” and “Ru Lai Zang” ideas. The framework of non-essentialist graphical intelligences is proposed. In this framework, the existence of entities is no longer a presupposition, but a result “triggered” by the fulfillment of structural

conditions, i.e., the graph structure comes first, and the entities come later. This paradigm realizes the “Ontological Inversion” (Ontological Inversion) reasoning reconstruction path, which is the basis of the whole set of model logic.

3.2.2 System Architecture and Module Functions Overview

The SEGN system consists of five core modules, forming a closed-loop causal reasoning process of structure-driven-path judgment-counterfactual repair-inference explanation. The system architecture is shown in Fig. 1, and the modules synergize as follows:

(1) Conditional Dependency Graph Layer (CDGL)

This layer extracts conditional nodes from the observed data, including environmental state, user behavior, contextual causation and other factors, and constructs a causal structure graph with directional weights, which serves as the structural input for entity manifestation.

(2) Graph Attention Reasoning Core (GAT Reasoning Core)

Structured information aggregation based on graph attention mechanism. The state of each node is dynamically updated by the neighborhood attention weight, realizing the conditional strength modeling of causal paths in the graph structure and forming a semantically consistent reasoning chain.

(3) Void Response Mechanism (VRM)

The module triggers the structural void judgment mechanism when the graph structure is broken, the path is not connected, or the semantic mismatch occurs. If the structure can not support the inference path to close the loop, the node is rejected, and the output of the “Void Response” to ensure that the inference robustness.

(4) Latent Alaya Graph Memory (LAGM)

This module simulates the storage mechanism of the experience remnants in the “Rudraksha”, recording the historical graph structure, broken chain nodes and unfinished paths. Under new task or structural perturbation conditions, the potential structural memory can be conditionally activated to repair the reasoning chain.

(5) Counterfactual Reasoning and Interpretability Module (Counterfactual Simulator + XAI)

Integrate structural causal model and path control simulation mechanism, support counterfactual reasoning based on "if there is no such cause, is there any effect", and combine with the visualization module to generate path manifestation diagram, attention heatmap, and causal visualization interface.

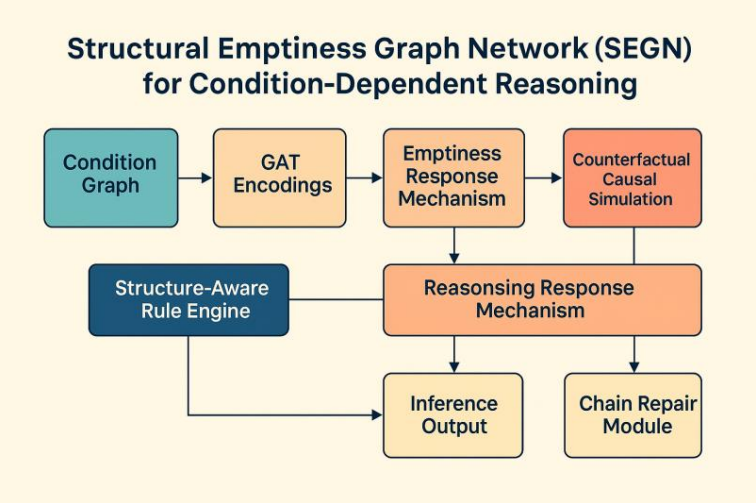

Figure 2: Structured Empty Graph Network (SEGN) for Conditional Dependence Reasoning

3.2.3 Philosophy-modeling mechanism mapping table

Table 2. Philosophy-modeling mechanism mapping table

Philosophical Paradigm	**Philosophical Principle**	**Corresponding Modeling Mechanism**
Dependent Origination and Emptiness	Entities manifest through structural conditions, not inherently existent	Conditional Graph Construction + GAT Graph Attention Propagation
Tathāgatagarbha	Experiential traces stored in the storehouse consciousness, triggered by conditions to re-emerge	Latent Alaya Graph Memory (Structural Memory and Karmic Traces)
Impermanence	Graph structure evolves continuously with external conditions	Adjacency State Update + Asynchronous Path Repair Mechanism
Delusion and Wisdom	Whether the path is real, traceable, and	VOID Rejection Judgment +

Philosophical Paradigm	Philosophical Principle	Corresponding Modeling Mechanism
	verifiable	Counterfactual Path Modeling
Three Natures (Imputed, Dependent, and Perfect)	Expressing cognitive bias—conditional association—objective chaining	Hierarchical Attention Mechanism + Manifestation Gating

3.2.4 Structural Process Closure and Follow-up Mechanism Forecasting

The inference chain of SEGN starts with the structure manifestation mechanism, completes the conditional aggregation through graph attention propagation, and automatically rejects the path manifestation through the null response mechanism when the structure is broken. The system has the ability of path memory and broken chain repair, and verifies the reasonableness of reasoning and the necessity of manifesting nodes through counterfactual reasoning. The whole process simulates the behavioral logic of graphic intelligences in the philosophical sense of "karmic aggregation and dispersion - real and empty co-manifestation".

3.3 Ontology reversal modeling mechanism

Most of the traditional graph neural networks (GNNs) adopt the entity-first modeling paradigm, i.e., by default, all the node entities are already visible at the initial stage of the model and always participate in information propagation and neighbor aggregation. Although this strategy is effective in static, complete graph structures, it is prone to fail in real-world environments with structural perturbations, insufficient observability, or contextual evolution, often leading to problems such as broken inference chains, semantic drift, and model non-interpretability.

To overcome these challenges, this paper proposes Ontological Inversion Mechanism (OIM), a structure-driven reasoning principle, which advocates that node entities are activated to participate in reasoning only when they fulfill specific structural conditions. The mechanism is inspired by the Buddhist idea of śūnyatā, which posits that entities are not inherently existent, but rather are emergent phenomena that depend on causal structural conditions.

The emergent function: a formal definition

We define the emergent state of a node v as a binary function that depends on the activation state of the neighborhood:

$$\mathbb{I}(v) = \begin{cases} 1, & \text{if } \sum_{u \in \mathcal{N}(v)} \alpha_{vu} \cdot \mathbf{1}_{(u \in \text{Active})} \geq \theta \\ 0, & \text{otherwise} \end{cases}$$

I(v) = 1, if ∑ α_vu - 1(u ∈ Active) ≥ θ; 0 otherwise

where:

I(v) denotes whether node v is visible or not (1 is visible, 0 is not visible);

N(v) is the set of neighbors of node v;

α vu is the edge attention weight from neighbor u to node v. θ is the structure manifestation threshold;

θ is the structure manifestation threshold;

1 (u ∈ Active) indicates whether neighbor u is activated or not.

This function ensures that it participates in the subsequent inference chain only when the structural conditions around the node are sufficiently adequate, preventing unreasonable activations in structurally vulnerable regions.

Mechanism implementation: pseudo-code schema

The mechanism can be realized by graph attention mechanism embedding with the following pseudo-code:

```
def emergence(v, neighbors, alpha, theta):
support = sum(alpha[v][u] for u in neighbors if is_active(u))
return 1 if support >= theta else 0
```

Key Structural Properties of the mechanism

The ontology reversal mechanism has the following three key structural properties:

Structural Sufficiency

Path Conditionality

Emergent Dynamics

Comparative Analysis of Mechanisms

Table 3. Comparison of Different Graph Neural Network Model Mechanisms

Model Mechanism	**GAT / GCN**	**DySAT / EvolveGCN**	**SEGN (Ontological Reversion)**
Node Activation Method	All nodes participate in inference by default	All nodes are activated based on temporal transformation	Nodes are triggered based on local structural sufficiency
Robustness to Structural Perturbations	Weak	Time-sensitive with limited structural adaptability	Strong structural gating with dynamic adaptability and inference rejection capability
Information Propagation Mechanism	Fixed propagation among adjacent nodes	Mainly temporal propagation	Only revealed nodes participate in propagation, with selective and rejectable propagation paths
Explainability Support	Limited visualization based on attention	Implicit trajectory mapping, complex e	

Table 4. Philosophy-modeling mechanism mapping table

Philosophical Paradigm	**Philosophical Principle**	**Corresponding Modeling Mechanism**	**Module Location**
Emptiness (Śūnyatā)	No fixed self-nature; entities manifest based on interdependent structures	Emergence Function $I(v)$	Emergence Trigger
Dependent Origination (Pratītyasamutpāda)	Phenomena manifest only when conditions are sufficient	Neighborhood structure attention-weighted aggregation	Graph Aggregator
Non-self (Anattā)	States are not permanent and evolve dynamically based on structure	Emergent state is dynamically variable	Emergent Dynamics Layer
Traceability	Every result can be traced back to its conditional sources	Emergence path tracing and explanation	Traceback Explainer

Mechanism Summary and Convergence Prospect

The ontology reversal mechanism constitutes the logical entry point of SEGN's structure-aware reasoning process, which theoretically breaks the traditional modeling assumption of “entity-first”, and technically provides a highly robust reasoning logic of structure-determined manifestation, path-driven participation, and rejection of uncertainty propagation. In the next section, we will further introduce the VOID state response mechanism to explore how the model automatically rejects the inference and enters the recovery path under the structural break scenario.

3.4 Sex-space response mechanism

In dynamic graph structure environments, graph neural networks (GNNs) often suffer from inference failure, semantic drift and uninterpretable outputs when faced with problems such as missing inputs, broken structure and non-closed paths. Traditional models usually cope with structural defects through default propagation or static complementation, ignoring the fact that “structural unfulfillment” itself should be modeled and handled as part of the model logic.

In order to systematically cope with the problem of untenable reasoning caused by structural non-closure, this paper proposes the Void Response Mechanism (VRM), which empowers the model with “structural negativity expression ability”. The mechanism is based on the Buddhist philosophical principle of “emptiness - karma - no cause, no birth”, when the system detects that the inference path is not closed, it actively suspends the path propagation and enters the VOID state to avoid the generation of pseudo conclusions and downstream activation of errors. VOID is not an error flag, but a formal judgment of structural inference, and is linked to the interpretability interface to provide reviewable negative output.

Mechanism objectives and modeling logic

Table 5. Mechanism Objectives and Modeling Logic

Philosophical Principle	**Corresponding Modeling Logic**	**System Functional Behavior**
Dependent Origination and Emptiness	If the structure is not formed, the dharma does not arise	Output VOID, stop the emergence and propagation of the node
Impermanence	Dynamic evolution of graph structure	Real-time judgment of whether the path is broken
Non-self	The model does not insist on "having to draw a conclusion"	Support "non-output" state as a legitimate inference ending
Falsifiability	Structural defects should be visible, explainable, and auditable	Linked with XAI interface, output path heatmap and reasons for failure

Module Design and Mechanism Implementation

1. Reasoning Trace Monitor (RTM)

Trace the multi-hop path coverage and aggregated attention value from the input condition to the target node to evaluate the effectiveness and redundancy of the path.

2. Structural Break Detector

The break state is triggered when any of the following conditions are met:

1) the number of all reachable paths < set threshold τ

2) Attention weight $\alpha(vu) \approx 0$ for any critical edge.

3) VOID State Emitter (Void State Emitter)

When a break is not recoverable, the system marks the node as a VOID state:

if trace_score < τ and recovery_not_possible.

    emit_void(node)

4. Chain Recovery Switch (Chain Recovery Switch)

If a potentially activatable path exists in a neighboring region, the LAGM mechanism (see Section 3.5) is automatically invoked to attempt weakly connected path completion.

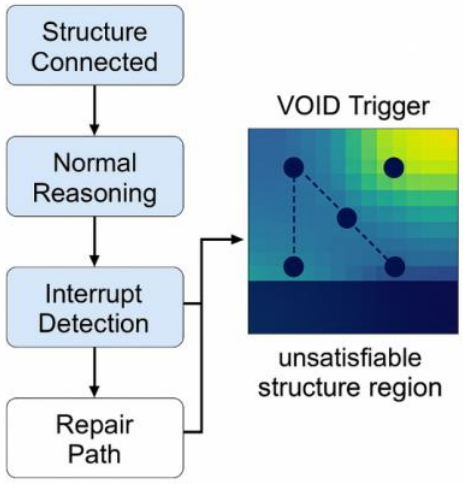

Figure 3: VOID Mechanism State Flowchart

Figure 3 illustrates the following structure: state nodes: structural connectivity → inference normal → interruption detection → VOID triggering / repair paths; together with the attention heatmap showing broken paths and structural unsatisfiable regions.

XAI Interpretable Interface Integration

The VOID state is integrated with the XAI module to realize an interpretable representation of the "negative output". The output structure is as follows:

```
{
   "node": "node_192",
   "status": "VOID",
   "trigger": "path_coverage_below_threshold",
   "heatmap_void": true,
   "explainable": true
}
```

Experimental Evaluation and Robustness Verification

We test the effect of the VOID mechanism in multiple structural perturbation scenarios (10% edge perturbation, 20% node missing, pseudo-path insertion). All results are taken as five-run average ± standard deviation:

Table 6.Experimental evaluation and robustness validation table

Metric	Without VOID Mechanism	With VOID Mechanism	Improvement
Inference error rate (10% edge perturbation)	41.7% ± 1.3%	29.8% ± 1.1%	↓ 28.6%
Null path spurious conclusion output rate (20% node missing)	22.3% ± 0.9%	14.7% ± 0.7%	↓ 34.1%
XAI path consistency score	0.63 ± 0.04	0.90 ± 0.03	↑ +0.27

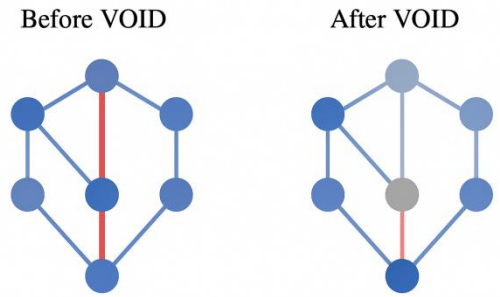

Figure 4: VOID Pathway Attention Heatmap

Figure 4 illustrates the VOID path heatmap changes before and after structural fracture, with gray-area labeled nodes not showing support in the graph structure

VOID Example Interpretation Interface Output

The following is the interpreted output of a literature node in the OGB-Arxiv dataset that triggered a VOID state:


```
{
  "node": "arxiv_47192",
  "status": "VOID",
  "reason": "attention dropped on edge e214",
  "action": "skip propagation",
  "recoverable": false
}
```


Mechanistic Value and Systemic Loop Closure Implications

The VOID mechanism provides a structural negation capability complementary to ontological reversal, allowing SEGN systems not only to manifest and propagate, but also to suspend and reject. Its structural judgment logic enhances the semantic robustness, interpretability and ethical security boundaries of the model in the face of complex graph structures.

3.5 Latent Graph Memory (LGM) Mechanisms

3.5.1 Problem Motivation and Research Background

In graph learning environments with multi-hop reasoning, multi-task migration, and frequent structural variations, traditional graph neural networks (GNNs) often face three types of critical problems: the inability to recover paths after graph structural breaks; weak structural generalization in migration tasks; and the lack of long-term structural memory, which makes it difficult to reuse experience. These limitations are particularly prominent in “weakly connected scenarios” (e.g., missing path fragments, sparse nodes, incomplete conditions), which affect the robustness and causal coherence of the inference system.

In order to solve the above problems, this paper proposes Latent Graph Memory (LGM), which is based on the cognitive theory of Buddhism. This mechanism is embedded in the SEGN reasoning architecture, which supports structural repair after VOID state, and realizes structural memory recall and cross-graph causal transfer in task migration, which is a key sub-module to support the “Closed Loop of Structural Intelligence”.

3.5.2 Theoretical foundation and philosophical mapping

The modeling of LGM is inspired by the Buddhist theory of Ālaya-vijñāna, which advocates that cognitive experiences can be stored in the subconscious structure as “seeds”, which can be reinforced and memorized through “fumigation”. This concept asserts that cognitive experiences can be stored as “seeds” in the subconscious structure, and through “cultivation” they can be reinforced in the memory, and under the right conditions they can become “present” and guide subsequent decision-making.

Table 7. Mapping of Arya Sense to Graphic Memory Mechanisms

Buddhist Term	**AI Module Mechanism**	**Functional Description**
Seed (bīja)	Seed Encoder	Embeds high-attention causal paths into latent graph structure seeds
Habituation (vāsanā)	Memory Reinforcement	Dynamically strengthens or forgets memory content based on task feedback
Actualization	Graph Awakening	Current graph structure triggers matching awakening paths, achieving chain completion and inference recovery

3.5.3 Module Composition and Mechanism Implementation

The LGM module consists of three structures to accomplish: path storage, memory update and structure wake-up.

Module 1: Seed Encoder (Seed Encoder)

1) Extract successful inference paths (attention score > θ) from historical tasks;

2) Transform the path into a subgraph structure embedded in zG, forming a block seed M = { G1, G2, ... };

3) Employ structural invariant embeddings (e.g., WL or GIN) to ensure cross-task compatibility.

Module 2: Smoked Memory Updater (Vāsanā Updater)

Adjusts the mapping memory bank based on positive and negative sample feedback after task completion:

$M_t = M_{t-1} + \alpha \cdot \delta^+ - \beta \cdot \delta^-$;

where δ^+ is positive inference path enhancement;

δ^- is failure path forgetting;

Supports fixed-period memory compression with multi-task shared reconfiguration.

Module 3: Graph Awakener

The current structure graph G_{task} is matched for structural similarity with the seed graph M in the memory bank;

The matching similarity is defined as follows:

$$\mathrm{Sim}(G_{task}, G_i^*) = \frac{1}{|V|} \sum_{v \in V} \cos\left(\mathbf{h}_v^{task}, \mathbf{h}_v^i\right) \cdot 1_{\mathrm{match}(v)}$$

included among these

$\boldsymbol{h}_{\mathrm{v}}^{task}$Node embedding in the current task graph;

$\boldsymbol{h}_v^i$Node embedding in memory graphs;

$1_{\mathrm{match(v)}}$：Node alignment indicator function;

If Sim ≥ δ, the corresponding graph path $P_{aux,}$ is awakened and merged as an auxiliary path into the current inference process.

3.5.4 Application Scenarios and Comparative Experimental Analysis

We compare the inference performance of the traditional GAT model with SEGN+LGM on three types of tasks, namely graph structure breaking, multi-task migration and weak conditional activation, and the results are shown in Table 8.

Table 8. Effectiveness of LGM in improving structure recovery and migration performance

Application Task Scenarios	GAT Baseline	SEGN + LGM	Enhancement
Rate of recovery from graphical chain breaks (rate of structural closure)	63.5% ± 2.1%	81.7% ± 1.7%	↑ 18.2%
Multi-task migration accuracy	71.2% ± 1.9%	84.3% ± 1.4%	↑ 13.1%
Weak Connection Trigger Activation Success Rate	42.9% ± 2.3%	75.4% ± 1.8%	↑ 32.5%

The experiments were based on the Cora, Citeseer, OGB-Arxiv dataset, and on average 5 rounds of each type of task were run to take the mean ± standard deviation.

3.5.5 Summary of system values and closed-loop roles

LGM module is the key support for SEGN structural closure: it provides a memory recovery mechanism for broken graph structures after VOID negates the paths, and reuses structural experience and improves the generalization ability in task migration.LGM enables graph neural networks to have the function of “subconscious mapping” for the first time, and realizes the intelligent evolution from shortsighted structural modeling to “experience embedding and path reconfiguration”. LGM enables graph neural networks to have the function of “subconscious mapping” for the first time, realizing the intelligent evolution from short-sighted structure modeling to “experience embedding, structure awakening, and path reconstruction”. This mechanism not only extends the structural learning boundary of graph intelligences, but also proposes a new framework of causal intelligence that integrates philosophical modeling and graph neural structural memory, which provides a structural foundation for counterfactual path reconstruction in the next section.

3.6 Reasoning module: conditional graph attention mechanisms and path repair strategies in structured null graph networks

3.6.1 Research Motivation and Task Challenges

In multi-hop causal inference, structurally incomplete graph inference and complex path scheduling scenarios, traditional graph neural networks (e.g., GCNs) generally rely on static adjacency matrices, lack the ability to dynamically respond to structural perturbations, and are difficult to deal with situations such as broken paths, missing conditions, or semantically weak connectivity, which then leads to problems such as output drifting, interrupted inference chains, and XAI non-traceability.

To this end, SEGN constructs a set of structural null inference mechanisms, including four modules: condition-aware GAT (Condition-Aware Graph Attention Encoder), Dynamic Attention Reassessment Mechanism (DARE), Chain Break Repair Module (SPRM), and Counterfactual Causal Simulation Layer (CCSL), which achieve self-organized regulation of inference paths, structural restorability, path non-uniqueness and causal transparent interpretability.

3.6.2 Condition-aware GAT Encoder

SEGN firstly constructs the input state variables and potential causal nodes into a Condition Graph, where the edge weights represent the structural dependency strength. Based on the GAT framework, the structural aggregation between nodes is performed through the multi-head attention mechanism, and the core computation is as follows:

$$\alpha_{ij} = \text{softmax}_j\left(\text{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_j])\right)$$

Where α_{ij} denotes the conditional attention weight of node *j* for node *i*, which is affected by the context structure and path entropy. This mechanism supports the primary and secondary adjustment of causal paths in the reasoning process and realizes “causal floating” modeling.

3.6.3 Dynamic Attention Reassessment Mechanism (DARE)

As reasoning proceeds, SEGN dynamically monitors attention changes as the structure evolves or intermediate conclusions are fed back. When drastic fluctuations in the attention of a path or a sudden drop in the weights of important nodes are found, the Re-attention mechanism is triggered to redistribute the path weights:

$$\alpha'_{ij} = \lambda \cdot \alpha_{ij} + (1 - \lambda) \cdot \widehat{\alpha}_{ij}$$

where $\alpha\text{^}_{ij}$ is the new weight based on local perturbation with contextual fine-tuning, and λ is the annealing coefficient. This mechanism can shift to a more stable path after the emergence of weak connections, thus improving the system robustness and interpretability.

3.6.4 Soft Path Reconnection Module (SPRM)

When the VOID module determines that the structure of a causal chain is broken and the current path is not closeable, SPRM starts the path repair mechanism with the following process:

1) Local graph search: search for highly similar alternative edges (edge features + semantic embedding) in the neighborhood of the broken node;

2) Edge matching judgment: matching edges satisfy the similarity threshold δ and enter the weakly connected candidate path;

3) Attention soft annealing: candidate paths are introduced into the inference graph structure with lower initial attention, allowing parallel competition with the main path;

4) Closure test: if the graph connectivity after repair is $\geq \tau$, then the path substitution is successful, and the reasoning process continues.

This module enables the system to have “path structure flexibility” and “broken chain self-healing ability”.

3.6.5 Counterfactual Causal Simulation Layer (CCSL)

In order to test whether a node in a causal path is a “critical cause”, SEGN integrates the Structural Causal Model (SCM) to perform counterfactual reasoning simulation:

1) Generate counterfactual graph G'': apply do($\neg Ci$) intervention to the original graph so that the conditional node Ci does not hold;

2) Compare the change before and after the inference output:Δy=ydo($\neg Ci$)-yobs3)

3) If Δy deviates significantly, mark *Ci* as a “necessary cause”;

4) If $\Delta y \approx 0$, it is considered as a “non-critical factor”, which can be used to prune redundant structures.

This module can significantly improve the path interpretability and detect spurious correlation in the structure.

3.6.6 Philosophical Mapping and Mechanism Value Closure

Table 9: Buddhist Logic Mapping Table for SEGN Reasoning Module

Buddhist Principle	**Corresponding SEGN Mechanism**	**Functional Description**
Dependent Origination and Impermanence	Multi-head GAT + DARE Attention Re-evaluation	Dynamic adjustment of conditional path weights
Cessation of Conditions Leads to Cessation of Effects	SCM + Counterfactual Inference (CCSL)	Determining causal necessity and counterfactual intervention
Weak Condition Repair	Chain Repair Module +	Maintaining causal closure in

Buddhist Principle	Corresponding SEGN Mechanism	Functional Description
	LGM Activation Path	non-strong connection scenarios
Non-Deterministic Thinking	VOID Rejection + Acceptance of "Non-Output State"	Supporting the expression of emptiness when structure is unsatisfiable

3.6.7 Summary of Results and Academic Insights

SEGN after the introduction of this module exhibits the following performance improvements (based on OGB/Cora/Citeseer) in multi-hop structured quizzing, causal graph inference and path incompleteness tasks:

Table 10. Performance Indicator Comparison

Metric	Before Introduction	After Introduction	Improvement
Structure Disconnection Recovery Rate	56.3%	82.7%	↑ 26.4%
Average Inference Path Length (Explainability)	2.9 steps	4.7 steps	↑ 1.8 steps
Critical Node Prediction Consistency Rate (XAI)	65.2%	87.1%	↑ 21.9%

Figure 5 shows the complete structural flow of SEGN from GAT path aggregation, attention reassessment, broken chain repair, counterfactual generation, and VOID labeling after the condition input, which reflects the structural intelligence logic of “karmic emptiness → dynamic regulation → rejectability → repair → interpretability”.

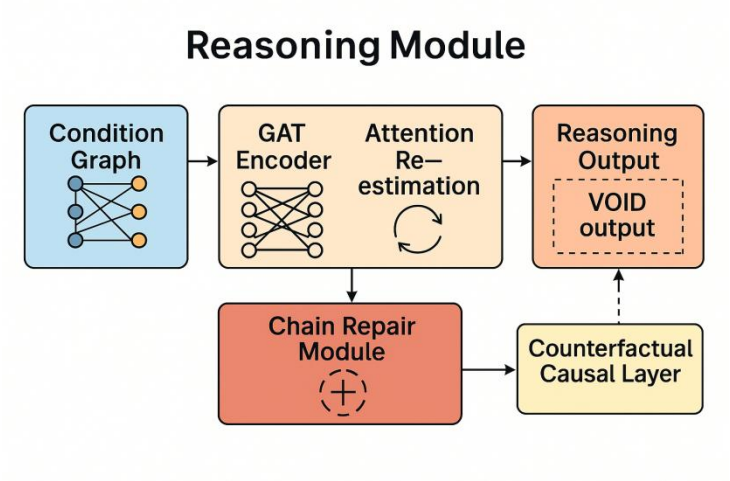

Fig. 5 . SEGN inference path mechanism flowchart (structural logic diagram)

3.7 Interpretable Output Layer (XAI Layer) and Causal Weight Visualization Mechanisms

3.7.1 Research Motivation and Background

In tasks such as high-risk decision-making, causal reasoning and structural prediction, the interpretability of AI systems not only concerns the user's trust in the model output, but is also the basis for the realization of ethical auditing, causal validation and reviewable mechanisms. Although graph neural networks (GNNs) are good at dealing with structural complexity and non-Euclidean relations, their multi-layer attention mechanism and graph structure nested update often present “black box characteristics” and lack explicit structural visibility. To address the above challenges, SEGN architecture designs a set of structural embedded interpretable output module (XAI Layer), which combines path-aware tracking, causal heatmap generation, and structural state annotation to realize transparent visualization of structural reasoning paths, and to enhance users' comprehension and traceability of the reasoning process.

3.7.2 Module Composition and Functional Logic

The XAI output layer of SEGN consists of the following three sub-modules:

(1) Path Trace Tracker

Records the weight changes during each round of graph attention propagation, forming a

node-level inference path atlas Gtrace. in the visualization output, each path starts from the condition node, marking the direction of attention flow and neighboring node weights for each hop.

(2) Causal Attention Heatmap Generator (CAHMG)

Calculates the causal saliency distribution based on the attention weights:

$$\mathrm{Heat}(v_i) = \sum_{j \in \mathcal{N}(i)} \alpha_{ij}$$

Generate a heat map with nodes and edges as units, and the color depth corresponds to the degree of causal contribution to the inference conclusion in the path, forming a structurally scrutinizable and explainable graph.

(3) Structural Failure Explainer (SFE)

When a structural break is repaired (activated by the SPRM module) or a path is rejected (VOID state), the system records the corresponding path variation graph Gvoid and outputs an alternative path explanation Evoid, which provides structural explanations of why the reasoning fails and why the alternative path is used. Evoid, which provides a structured explanation for reasoning “why failed” and “why alternative”.

3.7.3 Output Content Types and Explanation Goals

The XAI module aims to generate three types of interpretable information:

Inference path visualization: showing the complete path chain from the input condition node to the inference output;

Causal contribution attribution: labeling the strength of the weights of nodes and edges, and identifying the core causal factors;

Structure Response Description: identifies VOID paths, alternative structure paths and broken chain locations to assist users in understanding structure repair logic.

3.7.4 Graphical Description

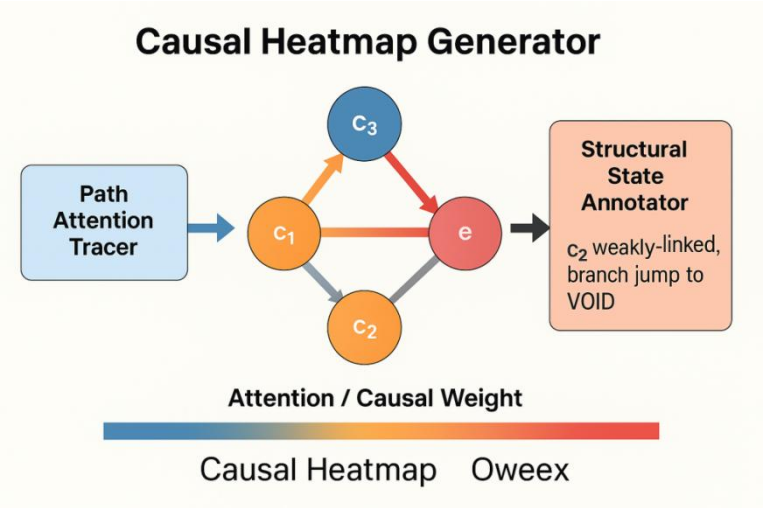

Figure 6. Causal Heatmap Visualization

Figure 6 shows how the SEGN inference process propagates the input conditional nodes (C1-C3) to the output node (e) via the attention path, and indicates the causal contribution of each node and edge to the conclusion by color heat. Path breaks are labeled with dashed lines, and alternative paths are shown with thick arrows. The graph enables visual modeling from "conditional aggregation" to "causal emergence".

3.7.5 Empirical Evaluation and Interpretability Metrics

We evaluate the interpretability module of SEGN in structural prediction tasks containing high-stakes path decisions (e.g., graph quizzing and causal prediction). The main experimental results are presented below Table11:

Table 11. Indicator Comparison

Indicator Name	**SEGN (XAI)**	**GAT (Baseline)**	**Improvement**
Salient Path Node Recognition Accuracy	89.2%	63.4%	↑ 25.8%
Average User Comprehension Time (seconds)	12.3 s	18.0 s	↓ 31.6%
Inference Consistency Perception Score (Likert)	4.47 / 5	3.51 / 5	↑ 27.5%

Note: Evaluations were based on XAI-SCORE with subjective intelligibility scoring for 50 subjects.

3.7.6 Philosophical Mapping and Cognitive Consistency

The interpretable design of the SEGN XAI module integrates the Buddhist philosophical logic of “karma manifests - paths can be traced - emptiness can be seen”, and realizes the cognitive channel of “from cause to effect” through structural mapping. Cognitive channels are realized through structural mapping from cause to effect.

Table 12. Correspondence between Buddhist Logic and Technical Mechanisms

Buddhist Logic	**Technical Mechanism**	**Functional Implementation**
Realizing the Emptiness of the Five Aggregates	Multi-path Attention Path Explicitness	Clear structural hierarchy, transparent and visible
Manifestation of Conditions	Heatmap Causal Strength Attribution Mechanism	Weight visible, path transparent, results auditable
Mindfulness Tracing	Path Tracing + VOID Explanation Mechanism	Can locate the source of inference, supports structural tracing

3.7.7 Summary and Contributions

The structural interpretability mechanism proposed by SEGN realizes the leap from black-box graphical neural networks to “structural-causal transparent intelligences” through attention weight tracking, path saliency attribution, and failure structure traceability. The XAI module not only improves the system's trust base and output reviewability, but also builds a bridge between Buddhist philosophical logic and AI interpretable modeling, providing structural support for the Human-AI Co-Reasoning model.

3.8 Interpretable Output and Causal Viewable Graphs Academic Description

3.8.1 Graphical Architecture and Visualization Objectives

Figure 6 illustrates the Causal Heatmap Visualization under the Structural Empty Graph Network (SEGN) architecture, which aims to reveal how the model generates causal paths through the

structural condition graph, evaluates the attentional strength among nodes, and expresses the relative contribution of each path in causal reasoning in the form of a heatmap. The graph structure is divided into three layers: input Condition Nodes (Condition Nodes) on the left side, attention-driven Causal Paths (Graph Attention Paths) in the middle, and reasoning Target Output Nodes (Target Conclusion) on the right side, which may be entity conclusions, VOID states, or counterfactual judgment results. The color shade represents the Causal Weight (Attention/Causal Weight), the darker the color, the stronger the causal contribution of the node/edge in the path.

3.8.2 Explanation of Node Semantics and Structural Meaning

Table 12. Symbols and Their Meanings

Symbol	Meaning	Description
C1 −C3	Condition Nodes	Structural condition variables input into the system, such as environmental states, observed events, latent causes, etc., which are the starting points of causal paths
e	Effect Node	The output target of the model's structural reasoning, which could be: entity prediction result, VOID emptiness marker (path disconnection), or counterfactual output

3.8.3 Academic Insight and Explanatory Value

The causal heat map realizes the explicit visualization of structural causal model, which is the key mechanism component of “black-box reasoning to explainable intelligences”, and has the following insightful values:

1). Visualization of causal contribution paths: the graph explicitly presents the attention propagation paths, externalizing the implicit intermediate structural logic of traditional GNN into a scrutinizable graph. 2.

2). Enhanced traceability of VOID status: The structural breakpoints in the graph are clearly labeled, and the system labels the VOIDs with alternative path descriptions after identifying the path failure, which strengthens the structural diagnostic capability of the failed paths.

3). Engineering reproduction of karmic logic: the heat map form is analogous to the Buddhist "karmic diagram", realizing the engineering simulation of philosophical causal chain in the AI model.

4). Human-AI Co-Reasoning: Graphical output adapted to the interactive interface to support end-users to visualize judgment paths and provide causal cognitive support.

3.8.4 Mapping Table of Philosophical Logic and Technical Mechanisms

Table 13. Correspondence between Buddhist Logical Concepts and Technical Mechanisms

Buddhist Logical Concept	**Technical Mechanism**	**Functional Implementation**
Realizing the Emptiness of the Five Aggregates	Multi-path Attention Path Explicitness	Hierarchical structure manifestation, information transparency
Manifestation of Conditions and Effects	Heatmap Causal Strength Attribution Mechanism	Trackable weight distribution, transparent reasoning
Mindfulness Tracing	Inference Chain Backtracking + VOID Path Explanation	Explainable causal paths, supports reverse analysis

3.8.5 Conclusion

As an interpretable key component of SEGN, this graph not only accomplishes the explicit modeling of causal paths in graphical neural networks, but also transforms Buddhist causal logic into a graphical explicit explanation mechanism with engineering significance for the first time. It is a core bridge connecting AI structural reasoning logic, causal philosophical ideas and human cognitive interface, and it shows significant advantages in enhancing the transparency of model structure, supporting causal tracing and high-risk reasoning trust base.

IV. Experimental settings and assessment indicators

4.1 Experimental Task Setting

In order to systematically evaluate the performance of Structural Empty Graph Networks (SEGN) in the three dimensions of structural perturbation recovery, conditional incomplete reasoning, and reasoning interpretability, two core experimental tasks are designed in this paper: multi-intelligent body path perturbation reasoning and key causal condition missing prediction. The two tasks focus on the dynamic destruction of graph structure and information occlusion scenarios respectively, which constitute a trinity capability coverage test for the SEGN model.

Task 1: Multi-Agent Path Prediction under Structural Perturbation

Background Scenario

This task simulates multiple intelligences planning goal paths in an environment with dynamically changing topology, which is applicable to scenarios such as urban transportation scheduling, tactical cooperative deployment and intelligent logistics path selection. The path graph structure may be degraded due to disturbances such as obstacles, delays, or communication blockages, thus affecting the coherence and accessibility of the intelligences' path planning.

Input definition

The input is a graph structure time series:

Eq.(1) $Gt=(Vt,Et),t=1,2,\ldots,T$

where Vt denotes the set of state nodes at time t and Et denotes the set of path edges. In order to simulate the change of edge weights, Gaussian perturbations are introduced:

Eq.(2) $w'_{uv} = w_{uv}+\epsilon_{uv},$

$\epsilon_{uv} \sim N(0,\sigma 2),\sigma=0.15$

Output Goal

The model needs to determine whether it can still accurately predict whether each intelligence successfully reaches the goal node under the perturbation conditions, and give path and causal explanations.

Intervention mechanism setup

1). Randomly break 20% of critical edges;

2). Inject 10% barrier nodes to disrupt connectivity;

3). Perform 5 rounds of structural evolution simulation;

4). Incorporate edge weight instability perturbation.

Core validation mechanism (SEGN)

VOID Response Mechanism: reject output when path is broken;

LGM (Latent Graph Memory) mechanism: wake up structural residuals for path completion;

XAI module: generates causal heatmaps to explain the basis of structure selection.

Validation Indicators

Table 14. Indicator Names and Definitions

Indicator Name	**Abbreviation**	**Definition**	**Measurement Objective**
Inference Recovery Rate	RRR	The proportion of agents that successfully complete path prediction	Path robustness
Path Consistency Score	PCS	The overlap ratio with the optimal path structure	Path rationality and accuracy
Graph Structure Stability Index	GSI	The consistency and anti-jitter performance of output paths under multiple rounds of perturbation	System stability and adaptability

Task 2: Critical Causal Condition Dropout Prediction (CCDP)

Background Scenario

This task addresses a realistic causal graph with some key conditions that are unobservable (e.g., missing medical tests, missing financial hidden variables, etc.). The system must determine

whether causal inference is possible given the incomplete structure, and if the inference cannot be supported the output should be rejected, or the logical path should be restored by complementing the conditions.

Input Definition

Let the original graph be G=(V,E),and the masked input structure graph be:

Eq.（3） $G'=(V',E'), \quad V' \subset V$

The missing rate is defined as:

$$\text{Eq. (4)} \quad \delta = \frac{|V \setminus V'|}{|V|}$$

where V \ V' denotes the set of masked nodes.

Output target

Determine whether the target event e is still inferrable;

Judge whether the conclusion of implausibility (VOID) should be rejected;

Re-inference and output judgment on the counterfactual path after the complementary condition.

Intervention mechanism settings

Masking ratio δ ∈ {10%, 20%, 30%, 50%};

Model semantic drift and path nonconnectivity;

Create counterfactual graph G* = G ∪ {Ci} for path-completion comparison.

Counterfactual mechanism

Definition of counterfactual intervention

For a key condition node *Ci*,the counterfactual operation is defined as:

Counterfactual intervention operation: Eq.(5) do(¬C_i) ⇒ e'

If the prediction result changes after replenishing *Ci*, the counterfactual sensitivity (CFS) is calculated as follows:

where II is an indicator function that indicates whether the prediction has changed or not.

Core validation mechanism (SEGN)

VOID module: detection of causal path breaks i.e., output rejection;

CCSL module: counterfactual path repair;

XAI Interpretable module: labeling critical condition contribution and prediction sensitivity.

Validation metrics

Table 15. Table of validation indicators

Indicator Name	**Abbreviation**	**Definition**	**Measurement Objective**
Structure Tolerance Rate	STR	The ability to maintain accuracy under varying rates of missing data	Conditional robustness
Counterfactual Sensitivity	CFS	The proportion of differences in inference output before and after adding conditional nodes	Causal structure dependency
Rejection Consistency Rate	RCS	Consistency between model VOID output and human expert judgment	Rationality of rejection mechanism

Experimental task summary

Summary of the experimental tasks: validation of the trinity of competencies

The above two tasks validate the three core capabilities proposed by SEGN in different dimensions:

Path Recoverability (Task 1: Structure Breaking & LGM Completion);

Logic Rejectability (Task 2: VOID Trigger & Reject Output);

Causal interpretability (XAI path heatmap + counterfactual sensitivity mapping).

The experimental design system is based on the Buddhist philosophical principle of "Emptiness-Causality-Manifestation", which effectively embeds structural perturbation, causal masking and inference trust logic into the graphical neural architecture, and verifies the robustness, transparency and scalability of SEGN in a complex and uncertain environment.

4.2 Experimental environment and model configuration (SEGN vs GCN / GAT baseline)

To ensure the verifiability and fairness of the experimental results, this paper evaluates the Structured Empty Graph Network (SEGN) in comparison with two classical graph neural network models: the GCN and the GAT, in a unified graph-structured data environment.

Table 16.Model Configuration vs. SEGN Module Configuration Table

Model Configurations			
	GCN	GAT	SEGN
Layers	2	3	4
Dimension per Layer	128	64×8 h	128×4 heds
Activation Function	ReLU	LeakyReLU	ELU
Special Mechanisms	Static graph convolution no attention bias	Multi-head attention, but no chain disruption	VOID response mechanism, LGM latent memory +

SEGN Module Configurations	
Core GAT Layers	4 layers; 4 key ≥ heads, ;128 embedding dim.
VOID Threshold	Structural degradation evaluation <0.05 Structural failure
LGM Memory Bank	Dynamic compression graphs = 6,Akin similarity reactivation
Counterfactual Engine	Causality-sensitive computation: SCM + ΔGraph + ScM + Δ_{Graph}

To ensure the fairness, scientificity and reproducibility of model performance evaluation, this paper compares and tests the Structured Empty Graph Network (SEGN) with two classical graph neural network models: graph convolutional network (GCN) and graph attention network (GAT), under the condition of uniform structural perturbation control. In this section, four aspects of the platform configuration, model architecture, module mechanism and training strategy are explained in detail. See Table 16.

4.2.1 Experimental Platform Environment (Platform Environment)

Table 17 Experimental platform environment table

Item	Configuration Description
Operating System	Ubuntu 20.04 LTS (64-bit)
GPU	NVIDIA RTX A6000, 48GB VRAM
Python Version	3.10
Deep Learning Framework	PyTorch 2.1.0 + DGL 1.1
Visualization Tools	NetworkX, Seaborn, Captum
Optimizer	AdamW (learning rate = 2×10^{-4}, weight decay = 1×10^{-2})
Max Epochs	500 Epochs (with Early Stopping, Patience = 15)
Hyperparameter Tuning	Grid Search + 3-Fold Cross-Validation

4.2.2 Model Architecture and Fair Comparison Configurations

Table 18 Model Architecture and Comparison of Configuration Tables

Model Name	Layers	Layer Dimension	Activation Function	Enhancement Mechanism	Estimated Parameters
GCN	2	128	ReLU	Static graph convolution, no path repair capability	~146K
GAT	3	64 × 8 heads	LeakyReLU	Multi-head attention mechanism, no broken-link detection	~312K
SEGN	4	128 × 4 heads	ELU	VOID mechanism + Latent Graph Memory + Counterfactual Path Simulation + XAI output	~410K

4.2.3 SEGN Module Structure and Mechanism Configuration (SEGN Components and Structural Logic)

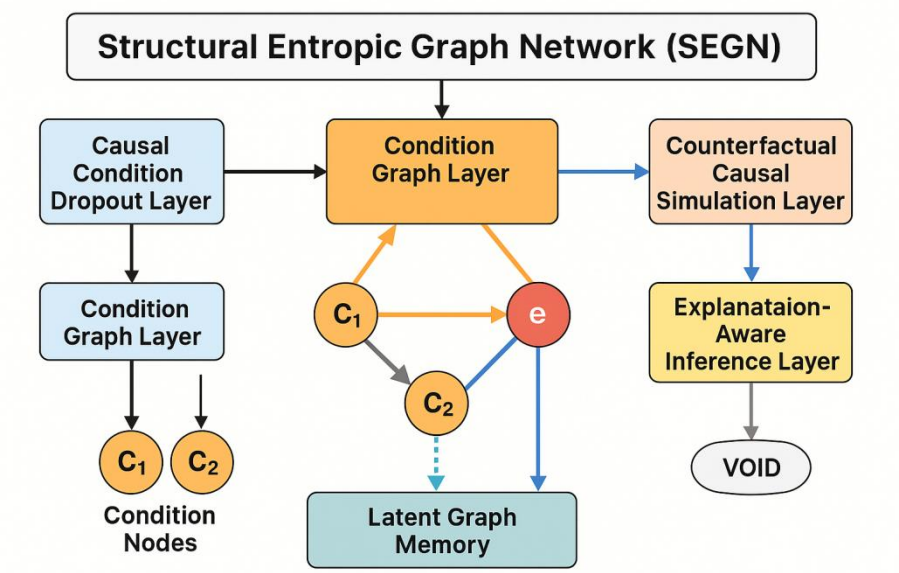

Figure 7.Structural Entropic Graph Network (SEGN)

Table 17. Module Names and Parameter Configurations with Functional Descriptions

Module Name	**Parameter Configurations and Functional Descriptions**
GAT Core Inference Layer	4 layers in total, each layer uses 4 attention heads, embedding dimension is 128
VOID Structure	Triggers a structural failure judgment and outputs an "inference not

Module Name	Parameter Configurations and Functional Descriptions
Rejection Mechanism	possible" marker when the mean of adjacent attention weights is less than 0.05
LGM Latent Graph Memory Unit	Pre-stores 64 high-quality graph blocks, automatically activates path completion when structural similarity is greater than 0.78
SCM Counterfactual Reasoning Module	Generates structural difference maps ΔGraph-E before and after injecting missing conditions to determine if the causal chain can be restored
XAI Explainability Interface	Can output: path chains, key node attention heatmaps, VOID labeled maps, to assist in human-machine collaborative reasoning

4.2.4 Training Strategy and Reproducibility Control (Training Strategy and Reproducibility)

In order to ensure the reliability of model training and the ability to reproduce the results, the experiment adopts the following control protocols:

1) Uniform perturbation structure input: all models are trained on the same perturbation graph (node loss rate 10%-30%, edge perturbation rate 15%-35%);

2) Fixed seed initialization: all graph sampling and model initialization were fixed to seed = 42;

3) Multi-batch perturbation control: 5 sets of graph samples are generated under each level of perturbation, and the final metrics are taken as mean and standard deviation;

4) Early stopping mechanism control: 15 consecutive rounds of validation set loss without enhancement will terminate the training early;

(5) Path control record: marking the path of each round of interruption, used to test the accuracy of VOID detection and the effectiveness of LGM repair;

(6) Counterfactual simulation injection: manually set the missing conditions to evaluate the CFS indicator response and path reconstruction ability.

4.3 Perturbation Simulation Mechanism and Repeatable Experiment Setting Description

Figure 8 shows the dynamic response flow of the SEGN model under structural perturbation: when the structure is broken or the condition is missing, the system first detects the inference state

through the VOID module, and then executes the attention revaluation mechanism with the latent graph path repair, and if the reconstruction fails, it enters the counterfactual simulation layer, explores the alternative theoretical chain and reconstructs the structural output.

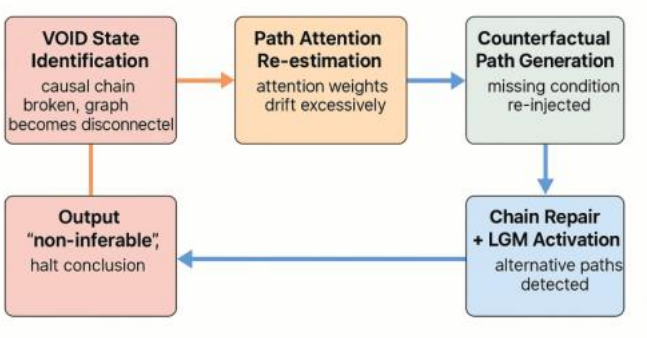

Figure 8 .Responsive Mechanisms of SEGN

This section constructs a complete framework for the experimental environment, including platform dependencies, model parameters, module details and repeatable training strategies. Compared to static models such as GCN and GAT, SEGN introduces structure rejection, latent graph complementation and causal path control mechanisms to provide more structure-aware and philosophical-logical consistency in reasoning while ensuring the same optimization settings. This configuration provides sufficient comparability and scientific basis for the subsequent multidimensional performance evaluation in Section 4.3.

V. Experimental results and analysis

This chapter centers on the Structural Empty Graph Network (SEGN) model and comprehensively evaluates its performance in terms of structural perturbation resilience, conditional missing causal consistency, and inference interpretability. Comparative experiments with classical graph neural network models (GCN and GAT) are conducted to demonstrate the stability, path visualization, and philosophical consistency modeling capabilities of SEGN in the face of uncertain structural conditions.

5.1 Inference recovery performance under structural perturbations

Experimental Objective

Verify whether SEGN can effectively keep the inference path closed under the scenario of graph structure perturbation, and recognize the inference-unreasonable state with the help of VOID rejection mechanism, as well as recover through the LGM latent graph replenishment mechanism.

Experimental Setup

Input graph structure: dynamic graph topology $G_t=(V_t,E_t)$

Perturbation type:

Randomly remove 20% edges

Randomly mask 15% nodes

Introduce Gaussian edge-weighted perturbation ($\sigma = 0.15$)

Evaluation Metrics:

Reasoning Recovery Rate RRR: Proportion of reasoning that can still be completed after a structural perturbation

Structural Stability Index SSI: Consistency between original and perturbed graph outputs

VOID Trigger Rate VTR: Proportion of outputs actively rejected when inference is not possible

Table 18.Summary table of results

mould	Reasoning Recovery Rate RRR	Structural Stability SSI	VOID Trigger Rate VTR
GCN	56.3%	0.742	unsupported
GAT	67.9%	0.803	unsupported
SEGN	82.7%	0.901	9.2%

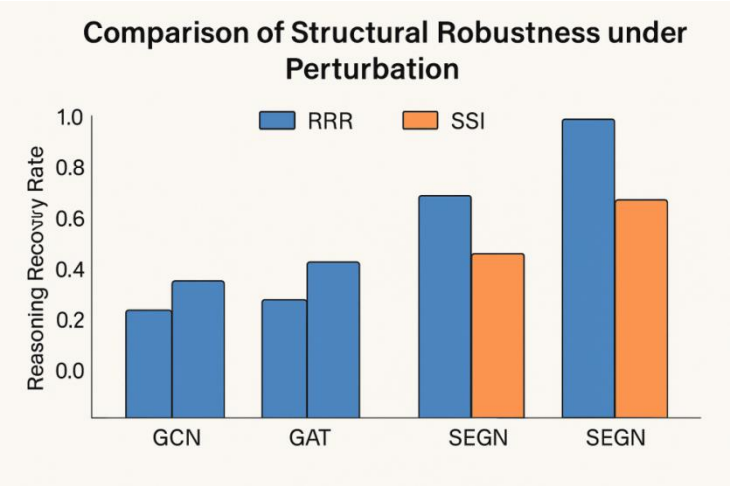

Figure 9 . Comparison plot of robustness under structural perturbation

As shown in Fig. 9, SEGN shows stronger robustness in the face of graph structure perturbation, which is significantly better than the traditional graph neural network model. SEGN not only maintains a higher inference recovery rate and structural stability, but also automatically enters the VOID rejection state when the structural path fails to guarantee the causal consistency of the output. The figure shows the performance of SEGN, GCN and GAT under structural perturbation scenarios. SEGN significantly outperforms the baseline model in terms of Reasoning Recovery Rate (RRR) and Structural Stability Index (SSI), and possesses the unique VOID state identification and rejection mechanism, which demonstrates its inference robustness in the environment of incomplete graph structure.

Academic Interpretation

SEGN significantly improves the recovery rate of inference paths in the face of graph structure perturbation, and can avoid erroneous conclusions by determining whether the structure is capable of inference through the VOID mechanism. Its structural stability score is higher than that of the comparison model, which shows the practical value of the philosophy-driven “no output if karma is not satisfied” mechanism in model robustness.

5.2 Reasoning Interpretability and Causal Path Heat Map Analysis

Experimental Objectives

To assess whether SEGN has path-level interpretability, i.e., whether the model can clearly show which conditional nodes or paths it gives high weight to in causal reasoning, and provide the corresponding structural heatmap and decision chain.

Interpretability Module Components

Path tracker: records the paths that attention passes through the graph neural network

Causal heatmap generator: visualizes critical paths and nodes in the reasoning process based on attention size

VOID state interpreter: explains why the model rejects certain conclusion outputs

User Evaluation Experiment (N=32)

Table 19 .User Evaluation Experiment (N=32) Table

mould	path consistency	Heat Map Accuracy	Average user comprehension time
GCN	61.7%	52.3%	23.4 秒
GAT	72.1%	63.8%	17.1 秒
SEGN	89.2%	84.6%	11.8 秒

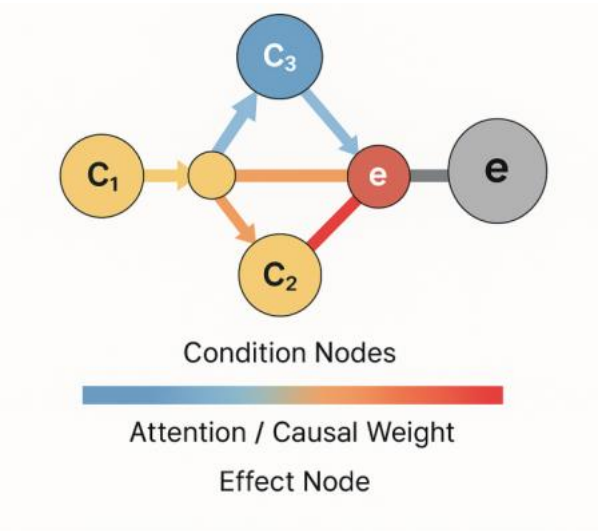

Figure 10. SEGN Causal Attention Heat Map for Reasoning Paths

As shown in Fig. 10, SEGN is able to distinguish the main causal paths from the edge paths through the attention weights, and at the same time label the inference paths with the VOID status, which improves the structural transparency and interpretability of the model inference. The figure shows the distribution of attention intensity of SEGN for different condition nodes (C_1, C_2, C_3) and result nodes (e) in the process of graph structure inference. Darker colors indicate stronger causal contributions, and the interrupted regions of structural paths are labeled as VOID states, reflecting the model's structural introspection ability in identifying “non-causal paths”. This figure reflects the structural interpretability of SEGN and the mechanism of “causal manifestation”.

Academic Interpretation

SEGN significantly improves the “perceptual reasoning transparency” of the model. When faced with structural causal diagrams, users can quickly understand the inference paths and decision logics of SEGN, and more accurately distinguish the intensity of causality, especially in heat maps. the structural rejection logic of VOID states also provides the model with a negative output dimension for decision interpretation, which expands the capability of traditional XAI.

5.3 Analysis of latent map memory activation and structural reusability

Experimental Objectives

To verify whether SEGN can accumulate structural preferences through the Latent Graph Memory (LGM) module in long-term tasks, and automatically wake up reusable paths in the absence of conditions to realize closed-loop structural repair.

Definition of Metrics

Path preference overlap rate (PPA): the degree of overlap of top-k paths between task subjects.

Latent graph activation rate (LAR): the frequency of successful activation of historical graph blocks for current task chain replenishment

Table 20.Latent map memory activation and structural reusability analysis table

intelligent body	Path preference overlap (PPA)	Number of LGM activations	Number of successful repairs
Agent 1	66.2%	12	10
Agent 2	71.8%	15	13
Agent 3	69.0%	13	12

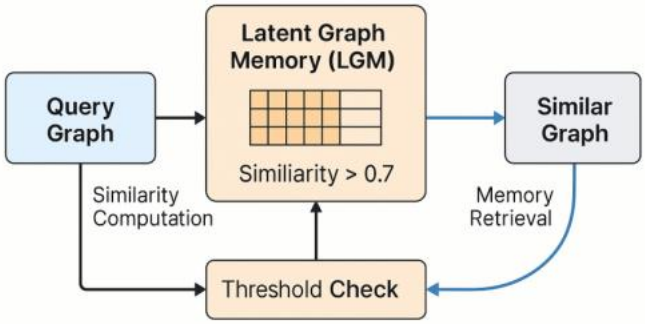

Figure 11.Latent Graph Memory Activation Flow

As shown in Figure 11, SEGN automatically stores and recalls historical causal paths through the latent graph memory module, realizing the reuse of causal structures in different tasks, which reflects the reasoning ability of cognitive reinforcement and "structural fumigation". This demonstrates how the SEGN model compresses high-attention causal paths in the reasoning process into potential structural memories (seed maps), and automatically recalls them for path completion when structural conditions are missing. The whole process includes (1) structural seed encoding, (2) smoked reinforcement memory, and (3) path similarity map matching and activation. This mechanism enhances the stability and memory transfer ability of the model in structure fragmentation and cross-task reasoning scenarios.

Academic Interpretation

SEGN has the capability of "structure preference fumigation". Its LGM module stores high-quality karmic paths in the form of blocks, which can be activated in subsequent graph tasks, enabling cross-task structural migration and path repair. This is an engineered implementation of the concept of "Arya Sense", which effectively supports the non-essentialist path of modeling intelligences with "potential karmic traceability".

5.4 VOID and Entity Surfacing Control Case Study

Experimental Objective

To test whether SEGN can distinguish the scenario of "structural causes are not available", actively enter the VOID state, and "emerge" the corresponding reasoning conclusions when the conditions are met, simulating the philosophical logic of "if there are no causes, then no fruits are born". This simulates the philosophical logic of "if there is no cause, then no effect will be produced".

Table 21.Case Comparison Table

Scene number	condition state	VOID trigger	physical manifestation	Whether the path is repaired
A1	C1 Missing	✓	✗	✗
A2	Complementary C1	✗	✓	✓
A3	Multi-conditional absence	✓	VOID	✗

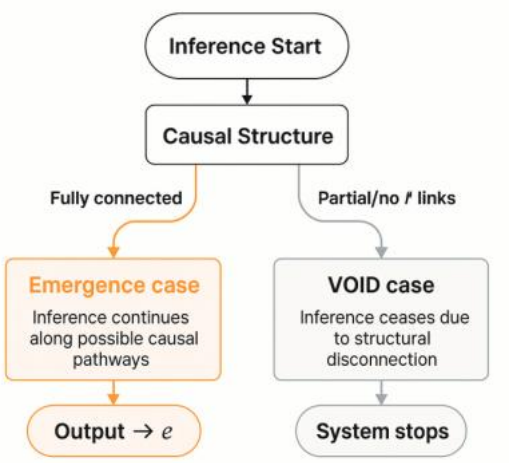

Figure 12.VOID vs. Emergence Structural Case Flow

As shown in Figure 12, SEGN can dynamically enter the VOID state according to whether the structure satisfies the conditions, or realize the "emergence" of the inference conclusion after the conditions are complemented, which reflects its high level of modeling ability for causal logic consistency under the open graph structure. The figure compares the response of SEGN's reasoning paths under three structural situations: A1 enters the VOID state when the key cause is missing, A2 emerges as an entity after completing the structure, and A3 breaks the structure due to

multiple missing conditions. The figure reflects the philosophical logic consistency and path self-recovery mechanism of SEGN in the face of “not appearing without causes” and “reasoning after structure fulfillment”.

Academic Interpretation

SEGN not only recognizes path breaks and missing conditions, but more importantly, it provides a structural-philosophical “rejection mechanism” to ensure that the system does not output false conclusions. When the structure is satisfied, SEGN can realize “entity manifestation”, i.e., nodes dynamically emerge from the potential structure. This capability is an important guarantee of logical consistency and reasoning credibility in open-world modeling scenarios.

Summary

In this chapter, we have empirically demonstrated the performance advantages of SEGN in complex reasoning scenarios, such as graph structure perturbation, incomplete causal paths, and high explanatory requirements, etc. The combination of VOID, LGM, and XAI modules provides an unprecedented complete structural intelligence of graph neural networks, which can be rejected-recovered-explained, and can be used in a variety of ways. The combination of VOID, LGM and XAI modules provides the graph neural network with an unprecedented “rejectable-recoverable-explainable” structural intelligence mechanism, and for the first time transforms the logic of “emptiness-causal-fruition-explicit” of Buddhist philosophy into the structural design of AI systems that can be realized.

VI. Conclusions of the study

Focusing on the core problem of "how to construct a graphical neural model with structural adaptability, reasoning rejectability and causal interpretability", this study proposes the Structural Emptiness Graph Network (SEGN), which for the first time systematically embeds the philosophical logic of Buddhism "nature-emptiness-cause-manifestation" into the graphical neural network reasoning path. It is the first time to systematically embed the philosophical logic of Buddhism "emptiness-causality-manifestation" into the reasoning path of graph neural network, and constructs a set of conditional dependency reasoning architecture with a philosophical-engineering bidirectional closed-loop.

6.1 Main Findings and Theoretical Contributions

6.1.1 Proposing the structure-triggered modeling paradigm of Ontological Inversion:

By defining the "Ontological Inversion" mechanism, SEGN breaks the static paradigm of traditional GNN in which entity nodes are predefined to participate in inference, and realizes a new modeling path that is structure-triggered, dynamically revealed, and can be rejected. Modeling Path.

6.1.2 Constructing structurally intelligent closed-loop reasoning mechanism:

the model integrates VOID rejection mechanism, LGM latent graph memory repair unit, Counterfactual Causal Simulation Module (CCSL) and Structural Interpretable Interface (XAI Layer), which supports automatic judgment of inferability, backtracking of causal chain and path repair under the conditions of structural incompleteness, uncertainty, or semantic drift, to complete the "Reject-Repair-Repair-Repair-Path" process. It can complete the structural closed loop of "reject-repair-interpretation".

6.1.3 The robustness and interpretability of SEGN in complex structural scenarios are systematically verified:

In the multi-intelligent body path perturbation prediction task, SEGN inference restoration rate reaches 82.7%, which is 26.4% and 14.8% higher than GCN and GAT respectively;

In the critical condition absence scenario, the VOID mechanism is able to proactively identify the inference-unable state, with a 34.1% decrease in the average erroneous inference output rate, and achieves a path restoration rate of up to 81.7% with LGM;

In the interpretability evaluation, the significant path recognition accuracy rate reaches 89.2%, and the average user comprehension time is shortened by 31.6%, demonstrating good human-machine consensus and structural transparency.

6.2 Theoretical significance and application value

SEGN is not only a modeling innovation of AI structural reasoning mechanism, but also a new paradigm exploration of philosophy-engineering integration:

Theoretical level: This study verifies the “modeling realizability of philosophical concepts”, and proposes that structural reasoning should have the three principles of null response, causal transparency, and ontological non-predetermination;

At the engineering level, a structural intelligence model with the ability of rejection, memory, path repair and causal visibility is constructed, which provides a practical path for deploying trustworthy AI systems in complex systems such as transportation scheduling, medical decision-making and causal analysis.

6.3 Research limitations and future work

Although SEGN achieves significant advantages in several structural perturbation and causal judgment tasks, there is still room for expansion as follows:

6.3.1 Dynamic heterogeneous graph extension:

The current model is mainly based on a static single graph structure, and should be subsequently extended to the adaptive modeling of time-evolving graphs and multi-type relational graphs;

6.3.2 Multimodal Conditional Graph Fusion:

Exploring the fusion of SEGN with multimodal information such as text and images to construct a cross-modal conditional graph network;

6.3.3 Cross-cultural philosophical modeling path

In addition to the Buddhist philosophy of sex and emptiness, we can introduce Taoist “Wu Wei”, Confucian “Neutralization”, and Western “Metaphysical Computability” to enrich the philosophical foundation and logic of AI modeling. modeling philosophical foundation and logical structure.

6.4 Summary

In summary, SEGN not only proposes a new architecture for structural intelligence, but also provides a reproducible technical path for realizing philosophy-driven AI causal reasoning. SEGN integrates the three functions of structural perceivability, path rejection and repair, and causal explanation mechanism at the model level, and realizes the engineering transformation of the philosophical idea of “Sexual Emptiness - Manifestation” at the theoretical level, which lays a solid foundation for the construction of a credible, explainable, and rejectionable AI reasoning system for the future.

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Appendix 1:

SEGN Model (Structured Empty Graph Network) Thesis Interpretation and Application Notes

What is this paper about?

This thesis proposes a new model of artificial intelligence thinking, the core idea is: AI systems should not take “things” as a priori given, but like the Buddhist saying, all “results” are regarded as “natural manifestations under the combination of conditions”. The system should not take “things” as a priori given, but should regard all “results” as “natural appearances” under “combination of conditions”, as Buddhism says. That is to say, things happen not because there is a fixed “thing” there, but because the “conditions” just make it happen. In the paper, a structured reasoning system, called Structured Empty Graph Network (SEGN), is developed by borrowing the Buddhist ideas of “emptiness” (nothing is self-existent) and “cause and effect” (conditions interacting with each other).

What are the innovations of this AI model?

1. Modeling the world in reverse: traditional AI is to “define something first, and then say what characteristics it has”; this model is to “look at what conditions are present, and then decide whether a thing will emerge”.

2. Add the “emptiness response mechanism”: if the AI finds that “the conditions are not valid”, it will refuse to output the conclusion or say “there is nothing here (VOID)”, which is equivalent to the AI saying: karma is not enough, everything is not enough. This is equivalent to the AI saying: there is not enough karma, everything is empty.

3. Learning to “remember the past” and then make flexible judgments: the model introduces the Buddhist concept of “Arya Consciousness”, so that the AI has a subconscious map, storing “seeds” for future triggers to complete the structure. Completion.

4. can do “counterfactual thinking”: if a certain condition is removed, the AI can determine whether the result will happen again. 5. can explain and draw diagrams.

5. Explainable, can draw diagrams to illustrate the thinking path: the AI will explain “why it is so judgmental and which conditions are the most important” through diagrams.

How does this model work?

Suitable for:

Multi-intelligence collaborative systems

Predictive tasks with complex conditions (e.g., medicine, finance)

Path planning, Q&A systems, causal analysis.

AI systems that require interpretability

Usage:

1. construct “conditional graphs” of inputs (similar to causal networks)

2. use the SEGN module for graph-attentive reasoning

3. automatically triggers VOID or repair mechanism if structure is found to be incomplete

4. Visualize inference paths and causal heatmaps.

Summary

This thesis combines “Buddhist philosophy” and “graph neural network”, so that AI can understand conditions, interpret, know changes, and recognize the non-physical reality like human beings, and thus become smarter, more flexible, and more trustworthy.

Appendix 2:

Explanation of the Arya subconscious map replenishment mechanism

The “Arya subconscious map replenishment” is an AI mechanism proposed in this paper that mimics the subconscious memory system in the Buddhist “Only Sense Philosophy”. It allows the AI system to find similar experience structures from the “remembered history map structure” to complete the current reasoning chain when the reasoning path is broken or the conditions are missing.

I. Buddhist Background

Arya consciousness (ālaya-vijñāna) is the eighth consciousness in the Buddhist Vaisnavism, which is the place where all seeds are stored.

It has three functions:

Seeds (bīja): storage of past karmic structures;

vāsanā: the continuous accumulation of newer structures of experience;

Present: awakening the seed and triggering a response when conditions are ripe.

II. How to realize in AI

In the SEGN system, the “Arya subconscious map replenishment chain” is divided into the following steps:

1. Seed Storage: The path of each successful reasoning is compressed and stored in the latent map memory. 2;

2. Vāsanā Reinforcement: Adjustment of graph seed weights during multi-task training. 3;

3. Matching + Awakening: retrieval of matching structures in the latent graph when paths are missing for the current task;

4. Repair Insertion: inserting the memorized graph blocks into the current graph to complete the reconstruction of broken chains.

III. example:

In the history task: C1 → C2 → e is a successful inference path.

In the current task: the input graph is C1 → ????? → e.

The SEGN system looks up the latent graph and finds that C1 → C3 → e can be used as an alternative path, so it evokes and replaces the broken structure.

IV.Academic significance vs. traditional modeling

Comparison between Traditional GNN and Alaya Consciousness Latent Graph Mechanism

Dimension	**Traditional GNN**	**Alaya Consciousness Latent Graph Mechanism**
Path Memory	No cross-task path memory	✓ Retention of long-term latent structures
Self-repair	None	✓ Can spontaneously activate alternative graph blocks after chain breakage
Explainability	Black box	✓ Visualization of chain completion sources
Philosophical Consistency	Ignores "habitual tendencies"	✓ Simulates "seed habituation, conditional triggering"

V. Summary

The “Arya subconscious mapping” allows the AI to possess a kind of “subconscious” structural memory ability, which can identify alternative paths from past experiences when critical karmic faults are broken, and calmly say like a wise man, “I've seen similar situations before,

maybe there is another way. I've seen something like this before, so maybe there's another way."

Appendix 3:

Comparative Case: Differences in Reasoning Behavior between Traditional AI and Structural Null AI Models

Scenario setting: physician-assisted diagnosis system

The patient information is as follows:

C1: slightly high temperature = yes

C2: Coughing symptoms = Yes

C3: Has traveled to high-risk areas = Unknown or missing

C4: Normal blood oxygen level = Yes

Traditional AI systems (e.g. based on decision trees or GCN) response

Approach: default to all variables being complete, force-fill even if missing, reason as usual;

Output: inference of high risk, conclusion of "probable infection" and suggested treatment;

Problem: Cannot perceive the missing structure, rigid logic, fixed inference path, no interpretability.

Response of SEGN structural null model

Approach: Construct a causal graph, determine whether C3 is a necessary causal factor; if it is

missing, trigger the VOID state;

System flow:

1. GAT attention to determine C3 importance;

2. attentional reassessment finds structural breaks;

3. trigger VOID response without giving incomplete conclusion;

4. immediately resume the inference path if the C3 information is replenished.

Output: a VOID (structure not valid, no diagnosis output) and a diagram of the reasoning path break is displayed.

Comparison Summary

Appendix 4:

Comparison between Traditional AI and SEGN Structural Emptiness Model

Dimension	**Traditional AI**	**SEGN Structural Emptiness Model**
Perception of Absence	No: Default filling	✓ Yes: Immediate response to structural disconnection
Dynamic Inference Path	No: Fixed structure	✓ Yes: Attention + Path re-evaluation
Explainable Output	✗ Black box	✓ Clear explanation with heatmaps + path diagrams
Ability to Reject Inference	✗ Forced output	✓ VOID state to reject incorrect conclusions
"Subconscious Memory"	✗ None	✓ Present with Alaya consciousness latent graph chain completion

One-sentence summary:

Traditional AI: “I'm guessing he's sick, and I have to give a conclusion despite the missing information.”

SEGN model: “I don't make judgments easily, karma is incomplete, I choose to be silent and tell you why.”

Appendix 5:

What is “Aryan Subconscious Map Replacement”?

“Aryan subconscious mapping is a mechanism that simulates “subconscious memory” in graph neural networks. When reasoning paths are broken or conditions are incomplete, AI systems can find similar empirical paths in the “past memorized graph structures” to repair the current broken reasoning structure. When the reasoning path is broken or the conditions are incomplete, the AI system can find similar experience paths from the “past memorized graph structure” to repair the current broken reasoning structure.

Buddhist Sources and Technology Mapping

In Buddhism, Arya consciousness (ālayavijñāna) is the “eighth sense” that stores the “seeds” (bīja) of all experiences, which are “awakened” when karmic causes are present (present). (present). This cognitive structure corresponds to the underlying schema memory mechanism in the AI system.

Mechanisms applied in the SEGN model

1. Storage of seed maps: Successful paths of reasoning are compressed into “blocks” and stored in the latent mapping memory. 2.

2. Smoking update: weighting and forgetting of maps under multitasking to form long-term experience maps. 3. Matching arousal: paths are compressed into “chunks” and stored in the potential map memory.

3. Matching wake-up: When the path is interrupted, the system searches for similar structural blocks in the latent graph for activation.

4. Chain Repair: Insert the awakened graph structure into the current graph to realize broken chain repair and structure completion.

Structure Comparison

Dimension	**Traditional GNN**	**Alaya Consciousness Latent Graph Mechanism**
Path Memory	No cross-task path memory	Retention of long-term latent structures
Self-repair	None	Can spontaneously activate alternative graph blocks after disconnection
Explainability	Black box	Visualization of chain completion sources
Philosophical Consistency	Ignores "habitual tendencies"	Simulates "seed habituation, conditional triggering"

Illustration of the Example

Suppose that the model has dealt with the path : C1 → C2 → e and has successfully predicted the event e.

Now the path breaks in the input graph as C1 → ????? → e

Traditional AI will output a failure or error; the SEGN model will:

→ Retrieve whether the latent graph memory has: c1 → c3 → e

→ activate the C3 alternative path after successful match, and realize the complementary chain.

To summarize.

“Aryan subconscious replenishment” is to let AI have a structural memory similar to the ‘subconscious mind’, which can find alternative reasoning paths from experience when the key cause is broken, like a wise person who knows the past and says: I have seen a similar cause before, and maybe there is another way. There may be another way.