Cognitive Interaction Layers for Neuro-Symbolic AI*

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Abstract

Despite recent breakthroughs in large language models (LLMs), current AI systems remain limited in their ability to engage with knowledge in ways that align with human cognition. While LLMs excel at syntactic and contextual processing, they often fall short in semantic interpretation, conceptual association, and memory-oriented reasoning. This gap underscores the need for cognitive interaction layers, which serve as human-AI interfaces that integrate structured knowledge with cognitive encoding strategies to support intuitive, interpretable, and memory-efficient learning.

This paper introduces a conceptual and technological framework for cognitive interaction layers that function as mediators between AI systems and human users. By embedding mechanisms such as semantic cues, associative representations, visual metaphors, and structured schemas, these layers enable more human-aligned interaction and knowledge transfer. We discuss the theoretical foundations of cognitive scaffolding and neuro-symbolic reasoning, provide a mathematical formulation of cognitive encoding and retrieval functions, and compare existing cognitive architectures with the proposed approach. The framework opens new avenues for human–AI interaction by transforming static knowledge representations into cognitively enriched environments that support education, skill acquisition, and interpretability in intelligent systems.

Keywords

cognitive interaction layer, human-AI interaction, semantic encoding, cognitive scaffolding, artificial intelligence, neuro-symbolic reasoning

1. Introduction

In the era of rapidly advancing artificial intelligence, the challenge of enabling machines to comprehend and reason in ways aligned with human cognition remains unresolved. Large language models (LLMs) demonstrate remarkable performance in syntactic and contextual processing, yet they continue to fall short in semantic interpretation, conceptual association, and memory-oriented reasoning [1]. These limitations highlight the need for cognitive AI systems that can engage with knowledge not only statistically but also meaningfully, by reflecting how humans naturally encode, retrieve, and apply information.

The study of human cognition provides valuable insights into how such systems may be designed. Jean Piaget [2] emphasized the stage-based progression of cognitive development, outlining how learners acquire and transform knowledge through structured interactions. Lev Vygotsky [3] further underscored the sociocultural dimensions of learning, introducing the Zone of Proximal Development as a space where guided interaction enables higher levels of reasoning. George Miller's [4] seminal work on working memory revealed constraints in human information processing, while Roger Schank and Robert Abelson [5] conceptualized scripts and schemas as memory-based structures guiding comprehension. Douglas Hofstadter [6] highlighted analogy-making as a central mechanism of intelligence, stressing the role of conceptual resonance and associative mapping. From a computational perspective, John Laird's Soar architecture [7] demonstrated how symbolic reasoning can be integrated with learning mechanisms, providing a foundation for cognitive architectures in AI.

ProfIT AI'25: 5th International Workshop of IT-professionals on Artificial Intelligence, October 15–17, 2025, Liverpool, UK

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Contemporary advances extend these foundations through the development of cognitive and neuro-inspired models in artificial intelligence, such as ACT-R, SOAR, and NARS, as well as neural simulations like Spaun and Leabra. Hybrid approaches in neuro-symbolic AI [8] combine structured reasoning with subsymbolic learning [9] to address tasks that demand both interpretability and flexibility. In parallel, research in prompt engineering and cognitive scaffolding [10] has explored strategies for guiding large-scale generative models with structured cues [11].
Against this backdrop, we propose the concept of cognitive interaction layers, interfaces designed to serve as cognitive mediators between humans and AI. Unlike conventional user interfaces, which primarily support functional interaction, cognitive interaction layers reflect how humans encode, retrieve, and associate knowledge. By leveraging mechanisms such as semantic cues, structured schemas, visual metaphors, and conceptual clustering, these layers aim to transform static representations into cognitively enriched environments that enhance interpretability, personalization, and knowledge transfer in human-AI interaction.

The development of cognitive artificial intelligence requires not only large-scale data and computational power but also new approaches to interaction and learning. One promising direction lies in the design of cognitive interaction layers is interfaces that support memory-oriented, associative, and categorization-based processes in human-AI collaboration.

Semantic encoding techniques have long been used in human learning to enhance memorability and recall. When integrated into adaptive digital environments [12], these strategies enable a form of semantic interaction [13] that is inherently bidirectional: it helps users acquire knowledge [14] while simultaneously enriching the cognitive models of the AI itself [15].Such interfaces provide a controlled yet flexible environment for supporting diverse information processing styles in people visual, auditory, and kinesthetic [16]. By embedding semantic cues and adaptive scaffolding into AI-driven systems, static knowledge representations can be transformed into dynamic learning experiences that promote both user comprehension and system adaptability.

This paper introduces a conceptual and technological framework for building cognitive AI agents capable of learning and reasoning through semantically structured and cognitively enriched interaction layers. The proposed approach supports knowledge formalization while fostering internal cognitive structures suitable for both symbolic and neuro-symbolic reasoning.

The development of intelligent interfaces to support cognitive interaction has advanced significantly in recent years, driven by breakthroughs in natural language processing (NLP), cognitive science, and adaptive user systems. Cognitive encoding strategies, long recognized as effective tools for memory and learning [17], have been increasingly embedded in digital platforms, where semantic scaffolds support personalized and adaptive education [18]. Human-in-the-loop learning has become a central paradigm [19], allowing AI systems to refine responses through interaction, thereby enhancing personalization and alignment with human cognition.

Transformer-based models such as BERT [20], RoBERTa [21], and GPT [22], have improved machine understanding of semantic and contextual relationships [23]. More recently, multimodal and fine-tuned models (e.g., MiniGPT-4, Hugging Face's PEFT libraries) have enabled systems capable of generating adaptive hints and feedback in real time. Adaptive interfaces [8] can dynamically adjust modality and complexity to match learners' cognitive load and style, while research into cognitively rich environments suggests that exposure to metaphor, narrative, and structured reasoning fosters the emergence of cognitive intelligence in AI [16].

Within AI research, cognitive and neuro-inspired models have sought to emulate aspects of human reasoning, memory, and abstraction. Symbolic cognitive architectures such as ACT-R, SOAR, and NARS provide structured frameworks, while biologically inspired models like Spaun and Leabra simulate neural processes. Hybrid approaches in neuro-symbolic AI [24], [8], [9] combine statistical learning with structured reasoning, offering interpretability and adaptability. Emerging paradigms such as cognitive graph learning and hybrid reasoning in LLMs extend this trend, aiming to balance pattern recognition with conceptual modeling [25].

A comparative overview of cognitive and neuro-inspired models relevant to the design of cognitive interaction layers is presented in Table 1. Symbolic cognitive architectures such as ACT-

R and Soar offer structured reasoning and interpretability, but limited integration with dynamic ontologies. Biologically inspired models, including Spaun and CLARION, capture aspects of human cognition such as implicit-explicit learning or spiking neural dynamics, though their scalability remains challenging. Hybrid approaches, including neuro-symbolic AI and cognitive graph learning, provide promising pathways to combine statistical learning with structured knowledge [26]. Large language models with reasoning traits, while limited in formal integration, serve as effective adaptive interfaces. Together, these models highlight both opportunities and limitations in bridging structured knowledge representation, cognitive encoding, and user-centered interaction design.

Table 1
Comparative overview of cognitive and neuro-inspired models relevant to cognitive interaction layers

Model/ Architecture	Key Features	Ontology/Structured Knowledge Integration	Interpretability	Cognitive Relevance
ACT-R	Modular symbolic model; production rules	Limited, via symbolic encoding	High	Strong for cognitive tasks
Soar	Rule-based cognitive architecture	Possible via rule definitions	High	Strong for problem-solving
Spaun	Large-scale spiking neural model	Difficult	Moderate	High biological plausibility
CLARION	Dual-process: implicit & explicit knowledge	Good integration via schemas	High	Models human learning styles
OpenCog	Semantic graphs + probabilistic logic	Native through AtomSpace graph structure	High	Supports analogy and reasoning
Neuro-Symbolic AI	Combines neural & symbolic reasoning	Excellent, supports hybrid pipelines	Moderate	Aligns with semantic AI
Cognitive Graph Learning	Enhances neural nets with semantic maps	Good	High	Suitable for conceptual reasoning
LLMs with reasoning traits	Transformer-based; contextual fluency	Weak formal integration	Moderate	Useful as adaptive front-end

Building on these models, we define the concept of a cognitive interaction layer as a cognitive interaction layer is a cognitively oriented human computer interaction environment that leverages cognitive encoding strategies to structure and present domain-specific knowledge. Grounded in cognitive psychology, these layers incorporate principles such as visual metaphors, chunking, and spatial schemas, which facilitate long-term memory formation and retrieval. These environments are informed by established principles in cognitive psychology, including visual metaphors, chunking, and spatial schemas, all of which facilitate long-term memory formation and retrieval.

When integrated into knowledge-based systems, cognitive interaction layers act as bridges between formal representations of knowledge and intuitive human understanding, thereby enhancing accessibility, interpretability, and learning in complex domains.

Cognitive intelligence refers to the ability of a system to interpret, associate, and manipulate abstract meanings rather than relying solely on statistical correlations or surface-level data [27]. In human cognition, this encompasses semantic integration, analogical reasoning, conceptual blending, and contextual understanding [28]. For artificial systems, achieving cognitive intelligence entails building internal structures that capture conceptual relationships and enable adaptive, meaning-based reasoning [8]. The development of such capacities requires moving beyond purely neural models toward architectures that support structured memory, symbol manipulation, and goal-directed learning [29].

The intersection of semantic knowledge representation, cognitive encoding, and neuro-symbolic modeling outlines a new paradigm for AI systems capable of reasoning in ways that resemble human cognition. Ontologies and structured knowledge graphs provide the semantic backbone, cognitive encoding strategies translate abstract representations into intuitive forms accessible to users and neuro-symbolic systems integrate statistical learning with symbolic manipulation. This layered integration fosters the emergence of meaning-aware agents that can interpret language, learn from contextual cues, and form adaptive associations.

In our approach, the semantic representation layer serves as the conceptual core, the cognitive interaction layer provides accessibility and alignment with human learning, and the neuro-symbolic component supports reasoning and adaptation. Together, these elements contribute to the development of AI agents with cognitive intelligence.

2. Mathematical Formulation

To formalize the concept of cognitive interaction layers, we define a minimal set of functions that capture the relationship between structured knowledge, cognitive encodings, and user interaction.

$$O=\{o_1,o_2,\ldots,o_n\} \tag{1}$$

The knowledge base O is defined as a set of domain concepts (e.g., terms, entities, or structured nodes).

$$f:O\rightarrow C, c_i=f(o_i), C=\{c_1,c_2,\ldots,c_n\} \tag{2}$$

A mapping function f assigns each concept o_i a cognitive representation, c_i such as a semantic cue, metaphor, or associative prompt.

$$D(o_i,o_j)=\alpha\cdot d_{sem}(o_i,o_j)+\beta\cdot d_{cog}(c_i,c_j) \tag{3}$$

A composite distance function D evaluates the similarity between concepts, combining semantic distance in the ontology with cognitive dissimilarity between encodings. Parameters α and β determine the weighting.

$$U(c_i)=\gamma\cdot R(c_i)-\lambda\cdot L(c_i) \tag{4}$$

A utility function U measures the effectiveness of a cognitive interaction layer, balancing retrieval success R against cognitive load L. Coefficients γ and λ control the trade-off between performance and mental effort.

Together, these equations provide a formal foundation for representing how knowledge is encoded, compared, and evaluated in a cognitive interaction environment.

3. Materials and Methods

Building on the formal definitions above, this section details the methodological framework and computational implementation.

The structured knowledge base O (Eq. 1) was instantiated as an ontology or graph. Each node represents a domain concept, which is mapped to a cognitive encoding ci (Eq. 2). Encodings are realized as semantic cues, spatial metaphors, or multimodal prompts to enhance interpretability.

The composite distance function (Eq. 3) was used to evaluate the alignment of knowledge structures with human-oriented encodings.

$d_{sem}\left(o_i, o_j\right)$ - semantic distance, calculated using graph-based ontology metrics.

$d_{cog}\left(c_i, c_j\right)$ - cognitive distance, representing dissimilarity in the chosen encodings (e.g., visual or semantic clustering).This formulation ensures that similarity is judged not only on formal relationships but also on user-oriented cognitive associations.

To enable hybrid reasoning, a neuro-symbolic integration function was implemented:

$$\Phi(x) = \lambda \cdot NN(x) + (1 - \lambda) KB(x) \tag{5}$$

The function *Φ(x)* balances statistical inference from a neural network *NN(x)* with structured reasoning from a symbolic knowledge base *KB(x)*. The parameter *λ∈[0,1]* adjusts their relative contributions.

This architecture allows flexible switching between data-driven pattern recognition and symbolic interpretation. Adaptive Reinforcement Encodings are updated dynamically based on user interaction:

$$c_i^{t+1} = c_i^t + \eta \cdot \nabla \; U\left(c_i^t\right) \tag{6}$$

Each encoding c_i is reinforced or modified according to the gradient of the utility function *U*. The learning rate *η* controls how strongly user performance influences the update.

This adaptive mechanism ensures that the system remains responsive to human feedback, progressively aligning representations with cognitive preferences.

The prototype of the cognitive interaction layer was developed as a conceptual visualization and interaction environment designed to enhance semantic accessibility and support associative learning. An algorithmic pipeline was constructed to map structured knowledge units into cognitive cues, including visual metaphors, conceptual clusters, and spatial organization. Particular emphasis was placed on ensuring consistency between semantic categories and their cognitive encodings, thereby aligning the interface with principles of cognitive psychology and human information processing.

The system architecture follows a modular design, enabling seamless integration of future neuro-inspired and neuro-symbolic components. Although the current implementation remains symbolic and rule-based, it was intentionally structured to support extensions with attention mechanisms, memory-augmented neural networks, and transformer-based models for context-sensitive adaptation. This modularity ensures scalability and flexibility, positioning the system as a foundation for next-generation cognitive AI frameworks.

The implementation was carried out using Python as the primary programming language. Structured knowledge bases were managed through RDFLib and semantic web standards, while the cognitive interaction layer was prototyped as a web application using HTML, CSS, and JavaScript. Natural language processing and semantic similarity computations were supported by transformer-based models (e.g., BERT variants from Hugging Face). The backend was implemented with Flask-based REST APIs, providing interoperability and extensibility for integration into larger ecosystems.The diagram below illustrates the flow of information within a cognitive interaction layer. The architecture can be conceptualized as a dynamic process that links structured knowledge, cognitive encodings, and adaptive updates. As shown in Figure 1, formal knowledge (e.g., ontologies or structured graphs) is mapped into cognitive representations such as semantic cues or associative prompts. These representations are then evaluated through an interaction utility function, balancing retrieval success and cognitive load, and are updated via adaptive reinforcement to reflect user performance and feedback.

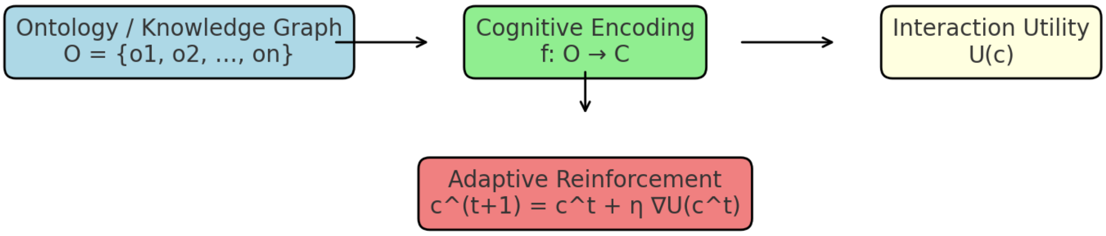

Figure 1: Flow of information in a cognitive interaction layer.

From an HCI perspective, the role of the human user becomes central in shaping and adapting the system. This human-in-the-loop perspective is illustrated in Figure 2, where the cognitive interaction layer aligns human memory and perception with AI reasoning through a bidirectional exchange. The user contributes memory, associations, and perceptual styles, while the AI provides statistical and symbolic reasoning capabilities. The cognitive interaction layer ensures alignment between these two, dynamically adapting to optimize comprehension, retention, and interpretability.

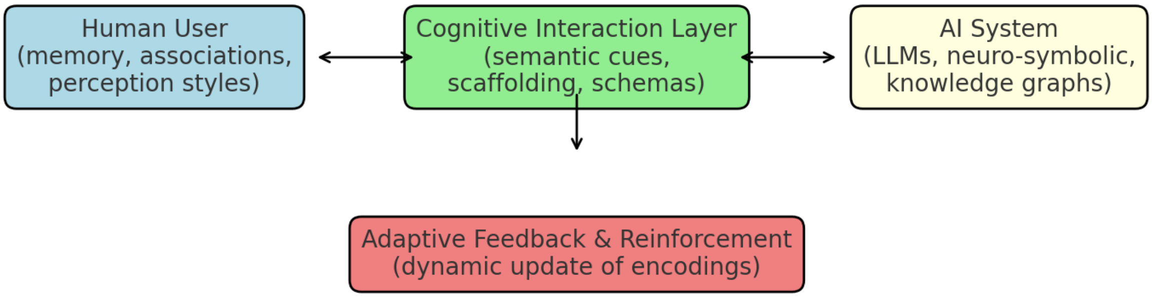

Figure 2: Human-in-the-loop perspective of cognitive interaction layers.

4. Results

A domain-independent knowledge base was formalized to capture key concepts and their semantic interrelations, incorporating hierarchical classifications, associative links, and metadata. On this foundation, a functional prototype of the cognitive interaction layer (Figure 1) was implemented to simulate user engagement and cognitive accessibility. The system maps structured concepts to cognitive cues using visual metaphors, conceptual clusters, and associative prompts designed to enhance recall and conceptual understanding. The interface provides an interactive visualization of conceptual networks, highlighting semantic coherence and logical structure, and allows simulated navigation through conceptual clusters and semantic pathways in an intuitive manner that supports associative learning and interpretability.

A cognitive agent model was developed to interpret domain-specific terms and infer contextual meaning using both structured knowledge and cognitive encodings. This model was tested in simulation scenarios, serving as a foundation for future empirical validation with human participants. The modular architecture supports integration of neuro-symbolic reasoning models, enabling adaptive learning and enhanced interpretability in subsequent iterations.

To illustrate applicability, the prototype was also instantiated on a pharmacology ontology containing domain-specific concepts and semantic relations. This demonstration shows how structured domain knowledge can be transformed into cognitively enriched interaction formats [30].

To provide a proof-of-concept evaluation of the proposed framework, we conducted simulation-based assessments in two benchmark scenarios a semantic similarity task and a recall-oriented learning task.

For semantic evaluation, the cognitive distance function was applied to standard benchmarks such as WordSim-353 and SimLex-999, measuring the alignment between machine-generated distances and published human similarity judgments. Simulation results suggest that the integration of cognitive encodings improves correlation with human ratings compared to purely semantic baselines.

For recall-oriented evaluation, a simulated learning task was implemented to model user interaction under two conditions a baseline interface and a prototype cognitive interaction layer enriched with semantic cues and visual metaphors. The simulation monitored recall accuracy and estimated cognitive load using NASA-TLX–inspired parameters. The proof-of-concept results indicate the potential of cognitive interaction layers to reduce cognitive load and improve recall compared to standard presentation formats.

These simulation-based evaluations are intended as illustrative demonstrations of feasibility rather than controlled user studies. They provide a conceptual foundation for more systematic experimental validation in future work.

5. Discussion

The proposed framework can be interpreted as a cognitive interaction layer, an interaction design paradigm that intentionally aligns computational processes with human memory structures, semantic associations, and retrieval mechanisms. By integrating structured knowledge representation with cognitive encoding strategies and cognitive modeling, this approach constitutes a novel direction in the development of interpretable AI systems. Unlike conventional semantic networks, it emphasizes meaning-making through human-oriented cues, enabling more intuitive and human-aligned interaction between users and AI agents.

Encoding complex terminology and abstract concepts through semantic cues, visual metaphors, and associative representations enhances recall and conceptual clarity for users, while simultaneously structuring information in a form that supports symbolic reasoning and contextual understanding for AI systems. In this way, the framework functions as a bidirectional scaffold: it facilitates human learning while enriching machine reasoning with cognitively meaningful representations.

Such an approach has strong potential for professional education and training contexts, where complex conceptual domains demand both precise recall and meaningful associations. Medical education is a prominent example, but the framework is equally applicable to engineering, law, or any field requiring semantic precision combined with cognitive support. Beyond education, the framework also contributes to explainability in intelligent systems by embedding interpretability at the level of interaction design.

At the same time, the current prototype remains limited by the scope of its knowledge base and by the preliminary stage of neuro-symbolic integration. Future development will focus on extending structured knowledge resources, refining cognitive encoding strategies, and incorporating neuro-inspired architectures capable of context-sensitive reasoning and adaptive learning. These advancements will further support the emergence of cognitive intelligence in AI agents, bridging the gap between statistical processing and meaning-oriented interaction.

While the proposed framework demonstrates promising outcomes in simulation, it is important to note its limitations. No controlled user studies were conducted, and the current evaluations are simulation-based demonstrations designed to illustrate feasibility. Future work will focus on empirical validation with human participants, including systematic experiments, larger sample sizes, and full statistical analysis of cognitive load measures such as NASA-TLX.

6. Conclusion

This paper has outlined a novel approach to the development of cognitive artificial intelligence through the design of cognitive interaction layers interfaces that align structured knowledge with human-oriented encoding strategies. The proposed framework provides a semantic and interpretable foundation that enhances both user comprehension and system-level reasoning. By embedding cognitive encoding mechanisms such as semantic cues, visual metaphors, and associative structures into interaction design, the framework supports the emergence of meaning-aware AI agents capable of more intuitive and human-aligned communication.

The results demonstrate the feasibility of integrating structured knowledge with cognitively enriched interaction, laying the groundwork for future integration with neuro-inspired and neuro-symbolic models. Such extensions will further enable the development of AI systems that combine statistical learning with symbolic reasoning and contextual understanding, thereby advancing the pursuit of cognitive intelligence in artificial agents.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT-5 (OpenAI) in order to: Grammar and spelling check. After using these service, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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