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The Impact of Neuro-Symbolic AI on Cognitive Linguistics

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ABSTRACT

Neuro-Symbolic Artificial Intelligence (AI) is indeed a fascinating domain, merging the structured reasoning of symbolic methods with the learning capabilities of neural networks. Its long-standing history reflects its significance in advancing AI towards achieving more robust and interpretable solutions. Neuro-symbolic AI is such an exciting and transformative field, as it combines the structured reasoning of symbolic AI with the adaptability and learning capabilities of neural networks. Your summary elegantly captures the breadth and depth of this growing discipline. The focus on representation, learning, reasoning, and decision-making is particularly critical, as these features define the capabilities of neuro-symbolic systems; Combines structured knowledge with data-driven insights. Merges symbolic frameworks with neural networks for adaptive systems. Implements robust symbolic logic for explainable outcomes. Guides systems in making informed and ethical choices. Neural-symbolic computation stands out as a compelling framework for bridging symbolic reasoning with the adaptive strengths of neural networks. Its foundation in cognitive models of reasoning, learning, and language offers a computational lens to explore and replicate human-like intelligence. Establishing a robust basis by combining logic-based symbolic systems and neural-based connectionist models to capture both structured reasoning and pattern recognition. Highlighting practical systems like cognitive computational tools that integrate machine learning and reasoning. These systems' impact ranges from biomedical applications (e.g., computational biology) to problem-solving in fault diagnosis and software verification. The need to address interpretability, scalability, and adaptability while ensuring the systems align with human cognitive processes.

Keywords: *Artificial intelligence, AI, Neuro-Symbolic, Psycho linguistics, Cognitive linguistics, Deep learning, Cognitive Psychology.*

INTRODUCTION

The study of human behaviour in the context of fields like computer science, artificial intelligence (AI), neural computation, cognitive science, philosophy, and psychology offers a rich interplay between cognitive modelling and computational techniques (Bhuyan et al., 2024; Belle, 2024). By presupposing that behaviour is largely governed by cognition and mental processing, these various disciplines share a common interest in understanding the mechanisms behind human behaviour and how they can be represented, simulated, or even replicated in machines (Hitzler & Sarker, 2022; Kumar, 2023).

Computational-logic systems focus on high-level reasoning and formalized thought processes (Votsis, 2024; Belle, 2024). They attempt to model cognitive reasoning using logical frameworks. Some key areas here are classical logic, which deals with well-defined reasoning rules and the relations between statements. Classical logic can model reasoning that follows strict, binary truth values (true/false), like syllogisms or propositional logic (Hitzler et al., 2024). Nonmonotonic logic extends classical logic by allowing for the possibility that the set of conclusions can be retracted in the light of new information. Human reasoning often involves revising conclusions as new information emerges (e.g., revising beliefs based on new evidence), which makes nonmonotonic logic an important tool for modelling this kind of dynamic reasoning (Bhuyan, 2025). Modal logic concerns reasoning about necessity and possibility. It enables us to make inferences regarding various states or conditions, such as "it is possible that…", or "it must be the case that…. This is particularly helpful for simulating mental states, including beliefs, knowledge, and intentions (Belle, 2024). Temporal logic is concerned with reasoning about time and temporal relationships. It permits the representation of things like "event A happens before event B" or "event A is always true at some time in the future," which are essential for modelling cognitive processes that depend on time or sequence (Oltramari, 2023). These logic models are of immense use in high-level cognition modelling, for instance, decision-making, reasoning, planning, and understanding human deduction based on the information they are given (Agrawal & Pandey, 2024).

Connectionist models, which are commonly known as neural networks, deal with lower-level cognitive dynamics (Thomas & Saad, 2022; Li et al., 2024). These models are motivated by brain architecture try to mimic how thinking arises from the interaction of brain cells (or artificial "nodes" in computational models) (Hossain & Chen, 2025). The most significant types are feedforward networks, or basic neural networks where information flows one way only, from input to output, without loops. They are used primarily for tasks like classification, pattern detection, and regression (Kishor,2022). Feedback loops are incorporated into recurrent networks, allowing the modelling of temporal dynamics, memory, and context-sensitive data. Recurrent networks, including Recurrent Neural Networks (RNNs), are necessary for sequence tasks, such as speech recognition or language modelling (Wan et al., 2024). Deep networks, or deep neural networks (DNNs), are composed of several layers of nodes (neurons) to form complex and hierarchical data representations. DNNs are utilized in applications such as image recognition, speech processing, and natural language processing (Keber et al., 2024).

Self-organizing networks, such as Self-Organizing Maps (SOMs), emphasize unsupervised learning and data organization without the use of external labels. These are especially valuable for clustering and pattern discovery (Alabi & Moarales, 2024). These connectionist models are essential for understanding the emergent processes of cognition, such as perception, learning, memory, and decision- making. The idea is that higher-level cognition emerges from the interactions of many simple processing units (neurons), much like the brain does (Bhuyan, 2025; Kumar, 2023).

Human cognition often involves uncertainty, ambiguity, and probabilistic reasoning, especially in real-world decision-making (Colelough & Regli, 2025). To model this, AI systems rely on probabilistic methods. Some key models of uncertainty include Bayesian networks, which use Bayesian inference to model uncertain relationships between variables. They are useful for representing systems where information is incomplete or noisy, such as predicting the likelihood of certain events given prior knowledge (Hitzler et al., 2024). Markov Decision Processes (MDPs) are used in decision-making problems, especially in reinforcement learning. MDPs help model situations where an agent is deciding over time in a stochastic or uncertain environment. Each action by the agent has a bearing on future rewards and states (Wan et al., 2024).

Markov Logic Networks (MLNs) blend first-order logic expressiveness with probabilistic reasoning. MLNs can represent complex relational domains where uncertainty is a core aspect, such as social networks or bioinformatics (Bhuyan et al., 2024). Probabilistic Inductive Logic Programs (PILPs) extend logic programming to include uncertainty and learning from data. PILPs integrate inductive logic programming (ILP), which aims at learning relations and rules from examples, with probabilistic reasoning (Belle, 2024). Such models of uncertainty are essential for modeling real-world cognition, wherein people often have to cope with incomplete, uncertain, or probabilistic information. By adopting these approaches, we can model human-like reasoning in AI systems that must make decisions under uncertainty (Hamilton et al., 2024). The unifying theme of all these models is that they try to capture varying degrees of cognition and mental processing within computational systems (Hitzler et al., 2022; Bhuyan et al., 2024). Computational-logic models are more interested in formalizing high-level reasoning, abstract thinking, and problem-solving (Belle, 2024). Connectionist models address lower-level functions such as pattern recognition, learning, and memory, drawing inspiration from the biological brain (Thomas & Saad, 2022).

Uncertainty models address the probabilistic and vague nature of real-world phenomena, allowing models to operate under uncertain conditions (Colelough & Regli, 2025). Collectively, these methods lead to a more integrated explanation of human behavior and computational modeling (Hamilton et al., 2024). As AI is developed further, the merger of knowledge from logic, neural computation, and uncertainty models will enable more advanced systems to reason, learn, and decide as more accurately resembling human thought (Hitzler & Sarker, 2022; Agrawal & Pandey, 2024).

LITERATURE REVIEW

The observation highlights a crucial intersection between artificial intelligence (AI) and psychology, particularly in how insights from brain cognition, behaviourist theory, and the philosophy of mind inform and shape the development of AI systems (Bhuyan, 2025; Hossain & Chen, 2025).

Brain Cognition and AI Development

AI development has often drawn inspiration from the human brain, particularly in areas like neural networks, which are loosely modelled after the structure and function of biological neurons. However, this replication is limited to physiological processes and struggles to capture the subjective, psychological aspects of human cognition (Thomas & Saad, 2022; Li et al., 2024). Human memory is inherently dynamic and influenced by emotional and contextual factors. Forgetting in humans is often passive and can even be counterintuitive—for example, the "ironic process theory," where trying to suppress a memory makes it more salient. In contrast, machine memory is typically designed for efficiency, with active deletion or overwriting of data. This fundamental difference highlights the gap between biological and artificial systems in simulating human-like memory processes (Hamilton et al., 2024).

Psychology as a Foundational Theory for AI

Reinforcement learning (RL) in AI is directly inspired by behaviourist psychology, particularly the work of B.F. Skinner and others. RL algorithms learn by interacting with an environment and receiving rewards or punishments, much like how organisms develop habitual behaviours through conditioning. This connection underscores how psychological theories can provide a framework for designing AI systems that learn and adapt (Bhuyan, 2025; Wan et al., 2024). One of the major challenges in AI is replicating human-like emotional responses and decision-making in ambiguous or uncertain situations. These capabilities are deeply rooted in psychological processes, such as affective computing (emotion modelling) and theories of decision-making under uncertainty. Advances in these areas will likely require deeper integration of psychological insights (Colelough & Regli, 2025; Hossain & Chen, 2025).

Philosophy of Mind and AI

The philosophy of mind grapples with questions about consciousness, qualia (subjective experiences), and intentionality—areas where AI currently falls short. While AI can simulate certain cognitive processes, it lacks the subjective experience that characterizes human thought. This limitation raises philosophical questions about whether machines can ever truly "think" or "feel" in the way humans do (Votsis, 2024; Hitzler & Sarker, 2022). The philosophy of mind also informs ethical discussions about AI, such as the moral status of AI systems, the nature of autonomy, and the implications of creating machines that mimic human behaviour. These considerations are critical as AI becomes more advanced and integrated into society (Kumar, 2023; Belle, 2024).

Challenges and Future Directions

Developing AI systems that can understand and respond to human emotions (affective computing) remains a significant challenge. This requires not only technical advancements but also a deeper understanding of emotional processes in psychology (Li et al., 2024; Bhuyan et al., 2024). Human decision-making often involves navigating ambiguous or incomplete information, relying on intuition, context, and prior experience. AI systems are poor at handling these subtleties, and advances in cognitive psychology might serve to open up avenues for enhancement (Agrawal & Pandey, 2024;

Colelough & Regli, 2025). The future of AI research will most probably rely on more integration between computer scientists, psychologists, neuroscientists, and philosophers. By combining knowledge from these disciplines, researchers can develop AI systems that are not only more powerful but also more human cognition and values (Hitzler et al., 2024; Thomas & Saad, 2022).

Human vs. Machine Processing: Internalized Knowledge and Emotion

Humans process external inputs in relation to internalized knowledge structures, which are informed by prior experiences, beliefs, and emotions (Oltramari, 2023). This allows us to perceive and respond tothe world subtly, e.g., in the sense of having attitudes, preferences, and affective reactions likesatisfaction, dissatisfaction, love, and dislike (Hitzler et al., 2022). Emotions are a critical componentof human cognition, contributing to decision-making, memory, and learning (Votsis, 2024).

For example,positive emotions like satisfaction reinforce certain behaviors, while negative ones like dissatisfaction cancause avoidance or alteration (Alabi & Morales, 2024). Machines, on the other hand, do not have inherent emotional experiences and arepre-programmed in terms of algorithms and data to interpret inputs (Thomas & Saad, 2022). While AI can simulate emotional responses based on sentiment analysis or affective computing, such responses are not grounded in subjective experience or internalized knowledge(Bhuyan et al.,2024).

Emotion as a Catalyst for Learning and Adaptation

Human cognitive psychology emphasizes the role of emotions in modifying internal knowledge structures (Kumar, 2023). For instance, if we are not satisfied, we would change our beliefs or behavior to achieve a better outcome (Hamilton et al., 2024). To replicate this process in AI, researchers can utilize emotion-tagged data to guide machine learning (Wan et al., 2024).

Reinforcement learning to associate certain outcomes with rewards or penalties, mimicking how human beings learn through affective feedback (Belle, 2024). Affective computing allows AI to measure and simulate emotional states to enable systems to adjust their behaviour to comply with human attitudes and preferences (Agrawal & Pandey, 2024). It is possible to program AI systems to update their internal models of emotional feedback, thereby "re-learning" and evolving in response over time (Colelough & Regli, 2025).

Challenges in Simulating Human Emotional Cognition

Human emotions are extremely subjective and context-specific (Hitzler & Sarker, 2022). The same incident can give rise to various emotional reactions in different people or even in the same person under different conditions (Keber et al., 2024). This nuance is a large challenge to capture in AI (Li et al., 2024). Though AI can learn on emotion-tagged data, these tags tend to be overly simplistic and miss the depth of human emotional experiences (Hossain & Chen, 2025). Further, emulating emotions in AI challenges ethical concerns regarding manipulation, deception, or misuse For e.g., should AI systems be made to simulate human emotions when they do not possess real understanding or empathy? (Bhuyan, 2025).

Applications and Future Directions

By integrating emotional responses and personal preferences, AI systems can be customized for specific users (Kishor, 2022).Recommendation systems already use preference data to personalize content, but integrating emotional feedback could make these systems even more responsive (Votsis, 2024). Emotionally intelligent AI could improve human-computer interaction, making AI systems more intuitive and user-friendly (Thomas & Saad, 2022). AI systems that understand and respond to human emotions could also play a role in mental health care, such as providing emotional support or detecting signs of distress (Kumar, 2023).

Interdisciplinary Collaboration

Advances in AI will require closer collaboration between cognitive psychologists and AI researchers (Oltramari, 2023). Cognitive psychology can provide insights into how humans process information, form attitudes, and experience emotions, while AI can offer tools for modelling and simulating these processes (Hitzler et al., 2022). The philosophy of mind can help address deeper questions about the nature of consciousness, emotion, and subjective experience, guiding the ethical and theoretical development of emotionally intelligent AI (Belle, 2024). This interdisciplinary approach is crucial for advancing neuro-symbolic systems that bridge symbolic reasoning with neural networks (Votsis, 2024).

Current Limitations of AI in Simulating Human Cognition

Human memory is associative, context-dependent, and influenced by emotions (Kumar, 2023). While AI systems can store and retrieve vast amounts of data, they lack the ability to form meaningful, context- rich associations or forget information in a human-like way (Bhuyan et al., 2024). Human attention is selective and dynamic, allowing us to focus on relevant information while filtering out distractions (Wan et al., 2024). AI systems, particularly those based on deep learning, struggle with tasks requiring selective attention or context switching (Thomas & Saad, 2022). Human perception is multimodal and integrates sensory inputs seamlessly (Hamilton et al., 2024). While AI systems are advanced in specific domains like computer vision, they often lack the ability to integrate multiple modalities holistically (Li et al., 2024). In addition, human intentions and emotions are greatly connected to subjective experience and the social environment (Alabi & Morales, 2024). While AI can mimic emotions using affective computing, they do not have a real understanding or empathy (Agrawal & Pandey, 2024).

The Role of Cognitive Psychology in Advancing AI

Cognitive psychology gives us a theory about how people process information, make decisions, and have feelings (Hitzler & Sarker, 2022). With the inclusion of such knowledge, AI researchers can create systems that better approximate human cognition (Colelough & Regli, 2025). Cognitive psychology highlights the central role of organized knowledge representation—e.g., schema and mental models—in human thinking (Oltramari, 2023). Similar methods, like semantic networks or graph representations of knowledge (Bhuyan, 2025).

Motivation, interest, and feedback based on emotions affect human learning (Kishor, 2022). AI systems can also be made to include the same mechanisms, for example, reinforcement learning with intrinsic motivation or exploration based on curiosity (Wan et al., 2024).

Key Research Directions for AI and Cognitive Psychology

Creating AI systems that are able to identify and understand human emotions is essential (Hossain & Chen, 2025). This entails affective computing that employs sensors and machine learning to identify emotional cues, and contextual awareness to better interpret emotions (Keber et al., 2024). Creating empathy in AI means knowing intentions and social relationships, which may be achieved by combining theory of mind—deducing other people's mental states (Belle, 2024)—and natural language processing to produce emotionally rich answers (Votsis, 2024). Human-like memory simulation involves creating contextual connections by means of associative memory (Bhuyan et al., 2024) and supporting lifelong learning for ongoing adaptation without catastrophic forgetting (Thomas & Saad, 2022).

Applications of Cognitive Psychology-Inspired AI (Expanded)

Recent progress in psychology-influenced neural networks has made more natural interactions between AI systems and humans (Shen et al., 2024). The systems now more closely mimic human attention patterns in visual processing tasks (Zehra et al., 2025). Experimental psychology approaches have also guided the creation of more interpretable AI systems for mental health applications (Taylor & Taylor, 2021), especially in simulating memory behaviors pertinent to therapy interventions (Shen et al., 2024). In addition, AI systems incorporating psychological models of comprehension now show improved performance in narrative text understanding (Diakidoy et al., 2014), enabling more sophisticated conversational agents.

Challenges and Ethical Considerations (Enhanced)

The intersection between psychology and AI has highlighted critical gaps in system explainability (Hoffman et al., 2022), especially in vision systems that attempt to mimic human perception (Zehra et al., 2025). Limitations in social robotics often stem from incomplete implementations of developmental psychology models (Sallami, 2021), particularly when tackling hierarchical reasoning tasks. Although AI has made significant inroads into creative domains, fundamental differences remain between human and machine creativity (Das, 2022), particularly regarding inspiration and conceptual development.

Future Prospects

Looking ahead, future systems may integrate biologically inspired cognitive architectures (Goertzel et al., 2010) with neuro-symbolic approaches to support more human-like reasoning. Psychology-inspired models for hierarchical attribute prediction (Li et al., 2022) indicate that future AI could develop capabilities for human-like aesthetic evaluation. Furthermore, combining natural language processing with psychology-inspired heuristics (Nunes et al., 2015) could enhance the transparency and accountability of AI decision systems.

Example of Cognitive Psychological Artificial Intelligence Applications

Cognitive psychology has indeed been instrumental in the development of AI, especially in modeling aspects of human cognition including attention mechanisms, memory processes, and problem-solving skills (Zhao et al., 2022). By emulating human cognitive processes, AI systems are becoming more sophisticated in natural language processing (Taylor & Taylor, 2021), image recognition (Li et al., 2022), and decision-making (Nunes et al., 2015). If you're examining the interaction between brain science and psychology in AI research, a number of important areas are worth investigation. One is neuro-inspired AI, whereby neural networks are inspired by the structure and function of the brain (Goertzel et al., 2010), with recent breakthroughs in spiking neural networks displaying particularly strong biological analogues (Shen et al., 2024). Attention mechanisms in AI, especially attention layers in deep learning, are motivated by human selective attention and focus (Zehra et al., 2025) and have changed computer vision and natural language processing. Memory in AI systems is another critical subject, where computational models simulate episodic and semantic memory present in humans (Saeed et al., 2023), especially for lifelong learning architectures (Colelough & Regli, 2025).

Emotion recognition is another prominent application, where AI systems analyze and respond to human emotions using psychological insights (Pravettoni et al., 2015), with wide-ranging uses from mental health screening to customer service (Luxton, 2014). Additionally, learning processes in AI often mirror reinforcement learning principles seen in human behavioral learning (Daróczy, 2010), especially in developmental robotics (Sallami, 2021).

Three specific application scenarios further illustrate these principles. In face attraction, AI systems utilize cognitive principles to analyze and assess facial features, expressions, and aesthetic preferences (Zhao et al., 2022). This is especially useful in social robotics (Bhuyan et al., 2024) and virtual avatars (Kumar, 2023), though challenges around cultural bias remain (Irshad et al., 2022). In affective computing, AI systems learn to identify, understand, and even mimic human emotions using gestures, voice tones, and facial expressions (Taylor & Taylor, 2021). This yields empathetic and responsive customer service systems (Agrawal & Pandey, 2024) and therapeutic systems (Hossain & Chen, 2025). Lastly, in music emotion applications, AI is trained to produce and process music in relation to emotional context (Das, 2022), which is being utilized for mood regulation, personalized music playlists, and therapeutic interventions, all grounded on psychological models of music cognition (Li et al., 2022).

Neural-Symbolic for Education: A Framework

The most important building blocks of neural-symbolic systems (NSC), as described by Garcez et al. (2009) and Bader and Hitzler (Besold et al., 2021), emphasize four core features. The first is the representation of knowledge, where symbolic knowledge is mapped to a neural network (Yu et al., 2023). The second feature, learning, is concerned with acquiring knowledge by the neural network from examples (Hooshyar et al., 2024). The third building block, reasoning, is about applying the acquired knowledge for problem-solving (Venugopal et al., 2021). Lastly, knowledge extraction is the retrieval of symbolic knowledge from the network (Garcez et al., 2009).

Key Components of the Neural-Symbolic Framework

During the translation algorithm stage, symbolic knowledge is added to the loss function of the neural network or initial architecture (Hooshyar et al., 2023). Bottom-clause propositionalising is one of the techniques employed to transform symbolic knowledge into propositional clauses (Besold et al., 2021). The neural learning algorithm entails updating the neural network with data while revising the theory from previous background knowledge (Hooshyar et al., 2025). Inductive logic programming (ILP) is especially effective here, utilizing NSC's learning ability to construct logic programs automatically (Yu et al., 2023).

Model-based methods or theorem proving are usually used for reasoning in neural networks (Zhang & Sheng, 2024). The knowledge acquired through learning optimizes the network and enhances the representation of problems (Venugopal et al., 2021). Once training is finished, the revised symbolic knowledge extraction takes place, with the algorithm being created to provide a true representation of the behavior of the network (Garcez et al., 2009; Hooshyar et al., 2024). An expert then gives feedback and analysis, examining the extracted knowledge and determining if it should be reintroduced into the system (Hooshyar et al., 2023)

Applications in Education

In forecasting students' risk of failure, online learning behavior data are used to forecast possible risks (Hooshyar et al., 2021). Concerns in this area include understanding the predictions and minimizing poor decisions (Hooshyar et al., 2025). Models become capable of making more accurate predictions and providing more understandable explanations with symbolic knowledge incorporated (Hooshyar et al., 2024). When choosing suitable physics students, models have a tendency to overestimate grades to the detriment of relationships in the subjects (Hooshyar et al., 2023). Incorporating symbolic knowledge enhances reasoning and decision-making (Venugopal et al., 2021).

Benefits of Neural-Symbolic Computing in Education

Neural-symbolic computing has several advantages. It makes it more accurate with the combination of data-driven learning and rules from the domain (Hooshyar et al., 2024). It makes it more explainable by the provision of clear reasoning (Hooshyar et al., 2021). It also improves efficiency through less dependence on massive training datasets (Yu et al., 2023).

Challenges and Considerations

Despite its benefits, neural-symbolic computing is not without challenges. One challenge is that it makes wrong predictions when symbolic knowledge is lacking (Hooshyar et al., 2025). Another challenge is data limitations and this may result in models that dismiss key educational guidelines (Hooshyar et al.,2023). Further, the process has a tendency to require the involvement of domain experts to interpret and validate the extracted knowledge (Garcez et al., 2009).

Visual Question Answering Application

In traditional approaches to visual question answering, limitations are that they necessitate large quantities of supervision and training data (Besold et al., 2021) and end-to-end reasoning based on none of them being separable one by one (Yu et al., 2023). The NSC approach negates these shortcomings via combining learning and reasoning (Hooshyar et al., 2024). It is divided into three primary steps.

1. First, neural learning employs convolutional neural networks (CNNs) to analyze visual scenes (Zhang & Sheng, 2024).
2. Second, semantic parsing uses recurrent neural networks (RNNs) to produce a symbolic program (Venugopal et al., 2021).
3. Third, symbolic reasoning runs the program on a structured representation of the scene (Garcez et al., 2009).

Advantages of NSC

The neural-symbolic method decreases the supervision needed (Hooshyar et al., 2023), enables interpretable and transferable solutions (Hooshyar et al., 2021), and allows for improved generalization across tasks and domains (Yu et al., 2023).

DISCUSSION

Machine learning plays a critical role in educational technology by enabling both cognitive and noncognitive student modeling. However, two major challenges persist in its application. First, there is the issue of limited training data. Models trained on large, generic datasets often fail to align with specific educational limitations, e.g., following proven learning principles or teaching guidelines (Agrawal & Pandey, 2024). Second, most machine learning algorithms are not understandable. Their black box nature can break the trust of educators, practitioners, and learners and make it hard for stakeholders to comprehend or verify the system's decisions (Colelough & Regli, 2025).

To address these issues, Neural-Symbolic Computing (NSC) has emerged as a potential answer. NSC mixes symbolic reasoning and neural learning, taking advantage of the strengths of both approaches. This hybrid solves uncertainty and shatters restrictions such as forgetting or bad extrapolation (Hitzler & Sarker, 2022). NSC enables previous knowledge to be incorporated, leading to improved learning and reasoning even with sparse data (Belle, 2024). Also, the explainability of these systems is significantly enhanced. Symbolic knowledge stored in the network can be leveraged and overlaid with comprehensible rules that are rendered explicit for teachers and students to have clear comprehension of the decision-making procedure. This renders them more reliable and deployable (Votsis, 2024).

Besides these general strengths, NSC is especially strong for purposes involving heterogeneous types of data. It is optimally suited to undertake operations such as assigning metadata to video or audio content and multimodal fusion for information retrieval (Thomas & Saad, 2022). Academically, NSC has enormous potential in many fields. In image and video processing, for instance, NSC supports emotional understanding as well as interpretable video action reasoning. This allows for the ability of AI to read visual content along with understanding human behavior and emotions, making educational content analysis value-added (Alabi & Morales, 2024). NSC in natural language processing assists in procedural text comprehension and relation extraction. The incorporation of symbolic reasoning guarantees more contextual understanding and adherence to educational goals (Keber et al., 2024).

Sequential tasking performance is also enhanced by NSC. It enhances knowledge tracing with deep learning structures such as Recurrent Neural Networks (RNNs), allowing the system to incorporate educational guidelines and follow learner development over time. This leads to more adaptive and perceptive learning systems (Wan et al., 2024). Overall, the argument posits a compelling future for artificial intelligence in calling for the incorporation of cognitive psychology within AI design. As such integration would allow AI not just to reason intellectually but also to have meaningful emotional interactions with people and other AI entities, this double capability—reflecting the logical "brain" and emotional “heart” of human cognition—holds the potential to advance AI toward more human-like communication and relational depth (Hossain & Chen, 2025).

Nevertheless, cognitive psychology also reveals the limitations of current AI. Variations in race, regional culture, environment, and subjective mental activity create inconsistencies that make it difficult to design universal, interpretable AI systems that truly reflect human cognitive processes (Bhuyan etal., 2024). In spite of all these challenges, the prospects are bright. The interdisciplinary synthesis of AI and psychology unlocks promising directions in big data healthcare, human-computer interaction, brain-computer interfaces, and general artificial intelligence. By embracing cognitive science and multimodal, high-dimensional data, these disciplines can mature in complementary directions, strengthening and complementing each other's strengths (Hamilton et al., 2024).

This investigation sets out a forward-thinking research trajectory. It places a premium on creating emotionally intelligent machines and richer human-computer interaction. The theoretical foundation and general applications potential emphasized here position NSC as a pioneering approach in AI research. By presenting this framework, the available literature offers significant direction for future scholars in attempting to develop the next generation of intelligent systems (Hitzler et al., 2022).

CONCLUSION

The conclusion appears to close the importance of conducting more research on the construction of interpretable AI models. More specifically, based on research results drawn from other areas of Neural Symbolic Computing (NSC), this constructed framework appears to be in the right direction in enhancing AI interpretability, especially in education. The future research, the execution of an NSCdriven approach oneducational datasets, appears like a feasible way to measure its impact and effic acy in learning.

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