REVIEW

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Artificial Intelligence, Representation, Language Models, Cognitive Science, and Applications in Psychiatry

Yapay Zeka, Temsiliyet, Dil Modelleri, Bilişsel Bilim ve Psikiyatride Uygulamaları

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Abstract

The paper explores the issue of representation in artificial intelligence (AI) by linking technical models (symbolic, connectionist/hybrid) with Wittgenstein's philosophy of language and delineates implications for cognitive science and psychiatric practice. The issue of representation remains at the core of developing trustworthy, interpretable systems and is closely tied with what is defined by AI—systems rationally behaving, human-like reasoners, or human-like actors. Representation formalisms hold, manipulate, and interpret knowledge in specific modes; shifting towards deeper learning and transformer constructions increased large language model's ability in processing natural language. Wittgenstein's picture theory and his language games open a window into how meaning is constructed in such models, making explainable AI imperative for transparency as much as for gaining trust. From a cognitive-scientific perspective, the key issue is how accurately AI can approximate human cognition. Skills such as multitask or few-shot learning or contextual inference are similarities between human learning abilities, but no current systems are in a position where they can interpret cultural context, "forms of life," or multimodal meaning. Future quantum computing, integration of neuroscientific signals (e.g., electroencephalogram), and multimodal pipelines would possibly redesign representational frameworks and generate contextually more sensitive systems. For psychiatry, symbolic, connectionist, and hybrid methods already include applications such as depression detection, risk prediction for schizophrenia, and enhanced social interaction for individuals with

Öz

Bu makale, teknik modelleri (sembolik, bağlantısal, hibrit) Wittgenstein'ın dil felsefesi ile ilişkilendirerek yapay zekadaki (YZ) temsil sorununu incelemeyi ve bunların bilişsel bilim ve psikiyatri pratiği için çıkarımlarını vurgulamayı amaçlamaktadır. YZ'de temsil sorunu, güvenilir ve yorumlanabilir sistemler geliştirmede karşılaşılan temel zorluklardan biridir. Bu sorun, YZ'nin tanımıyla yakından ilişkilidir ve rasyonel davranış, insan benzeri düşünme ve insan benzeri davranış yaklaşımları üzerinden ele alınabilir. Sembolik, bağlantısal ve hibrit modeller gibi temsil yöntemleri, bilginin kodlanması, işlenmesi ve yorumlanması için farklı mekanizmalar sunar. İstatistiksel yaklaşımlardan derin öğrenme ve transformer tabanlı mimarilere geçiş, büyük dil modellerinin doğal dili işleme yeteneklerinde önemli ilerlemeler sağlamıştır. Wittgenstein'ın "resim kuramı" ve "dil oyunları" yaklaşımları, bu modellerde anlam inşasını anlamak için kavramsal bir çerçeve sunar. Açıklanabilir YZ, şeffaflık ve güvenin artırılması açısından kritik bir yaklaşım olarak öne çıkmaktadır. Bilişsel bilim perspektifinden, YZ'nin insan bilişsel süreçlerini ne ölçüde taklit edebileceği konusu önemli tartışmalardan biridir. Çoklu görev öğrenme, az örnekle öğrenme ve bağlamsal anlam çıkarma gibi yetenekler, insan zihninin öğrenme biçimleriyle benzerlik gösterse de, YZ hala kültürel bağlamı, yaşam formunu ve çoklu modalite üzerinden anlamı tam olarak yakalamakta sınırlıdır. Gelecekte kuantum bilişim, sinirbilim verilerinin (örn, elektroensefalogram) entegrasyonu ve çoklu modalite sistemleri, temsil stratejilerini yeniden şekillendirme ve

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Abstract

dementia. Advancements for psychotherapy-directed descriptions of language can further raise utility. Integrating philosophical, technical, and clinical perspectives on representation can guide design for more interpretable, safe AI with clinical utility in psychiatry.

Keywords: Artificial intelligence, cognitive science, large language models, psychiatry, representation, Wittgenstein

Öz

YZ'yi bilişsel bilim ile bütünleştirerek daha insan benzeri, bağlamı yakalayabilen yetenekler kazandırma potansiyeline sahiptir. Bununla birlikte, psikiyatri uygulamalarında kullanılan sembolik, bağlantısal ve hibrit yaklaşımlar oldukça önemlidir. YZ'nin depresyon tespiti, şizofreni riskinin öngörülmesi, demans bakımında sosyal etkileşimin artırılması gibi çok çeşitli klinik uygulamaları mevcuttur. Psikoterapi ve dil temsili alanındaki gelişmelerin gelecekte YZ'nin psikiyatrideki işlevselliğini artıracağı öngörülmektedir. Genel olarak, temsil sorununa ilişkin felsefi, teknik ve klinik bakış açılarının bütünleştirilmesi, psikiyatride daha yorumlanabilir, daha güvenli ve klinik açıdan daha yararlı YZ sistemlerine giden bir yol haritası sunar.

Anahtar kelimeler: Bilişsel bilim, büyük dil modelleri, psikiyatri, temsil, Wittgenstein, yapay zeka

Introduction

A review of the literature reveals that artificial intelligence (AI) has persisted as a field that has intensively utilized engineering, linguistics, cognitive science, philosophy, and neuroscience since the mid-twentieth century. Alan Turing's question in 1950, which surprised most people, "Can machines think?", has led to interesting and surprising results in people's minds. Turing's question marked one of the earliest conceptual turning points in AI research sparking lasting debates on machine intelligence and cognition (1). The rise of computer science and technology has been highly significant. As algorithms began mimicking how our minds and language work, AI evolved from just a technical field to one that looks at modeling key aspects of human thought like language, reasoning, memory, and decision-making. Over time, various ideas about AI emerged, shaped by studies in language and philosophy, alongside rapid technological advancements. In this context, the concept of representation how AI systems gather, organize, and apply knowledge about the world has been explored in depth.

Language ability is one of the most important capacities that distinguish humans from other primates. Language also constitutes one of the most fundamental cognitive abilities of the human mind and plays a central role in thinking, communication, information sharing, and social interaction. Such an important human ability cannot be addressed in isolation from discussions about its representation in AI. Analyzing language solely as a means of expression would be insufficient. Language can also be described as an element that embodies the semantic and representational dimensions of objects and events in the world. For AI systems to resemble human cognitive abilities, or at least mimic them, they must incorporate language-based representation mechanisms. Accordingly, language processing in AI research is not only a technical challenge but also an area where philosophical and linguistic questions related to meaning, context, and cultural intertwining arise. AI architectures predominantly use language models. These language models are designed to process, interpret, and generate human language. Recently developed large language models (LLMs) have significantly advanced natural language processing (NLP) by demonstrating high performance on language generation and comprehension tasks (2). LLMs are now important tools that most people are aware of. They have permeated almost every aspect of our lives. These discussions and developments necessarily entail philosophical considerations. Philosophy, and especially philosophy of language, is inevitably part of the process. From the perspective of the philosophy of language, these developments must focus on theories of language, particularly the relationships among language use, meaning, and context. In this context, it is inevitable to revisit Ludwig Wittgenstein's approaches.

Recently, the latest deep learning approaches built on NLP have become quite popular. These approaches are highly functional and efficient. They are logic-based and rule-oriented models, and their importance in this field is growing due to their transparency and interpretability (3). Language ability is seriously related to logical representation. Of course, emphasizing this relationship alone is not sufficient. But representing language with formal logic is very important. This representation contributes significantly to revealing the abilities of explicit semantic inference and structured reasoning, which are still challenging for data-driven systems. Historically, AI research has encompassed several fundamental approaches to language processing.

Generally, these consist of N-gram models, recurrent neural networks (RNN), and transformer-based architectures (4). All of these approaches are used in the creation of today's AI models. In particular, the models include data-driven methods based on statistical learning from large data sets. They also include rule-based mechanisms that process symbolic and logical representations of meaning, which is important for our topic. Each approach offers different advantages and limitations, particularly in terms of semantic precision and contextual understanding. NLP, initially developed as one of AI's most dynamic subfields, was built using linguistic theory and cognitive models aiming to simulate human language comprehension. Over time, especially with the increasing effectiveness of deep learning methods, this field has shifted towards a paradigm focused on technological developments aiming for high- performance expectations. LLMs trained on large datasets have achieved remarkable success in tasks such as text generation, translation, summarization, dialogue, and question answering. However, whether such systems truly capture semantic understanding or primarily reflect statistical regularities inherent in language use remains a subject of debate (3,5). They can't capture human cognition and language capacity at this level. Perhaps we will reach a more perfect point in the future. But for now, it does not seem possible to express this. In fact, this article focuses on how this goal can be partially achieved in some areas. In addition to these developments, AI is increasingly able to mimic human cognitive abilities in areas such as memory, attention, problem-solving, and decision-making. Given these capabilities, it has the potential to deepen and enhance existing human capacity (6). In light of these developments, particular emphasis should be placed on the mutual interaction between AI and cognitive science. Advances in the study of human cognition provide information for the design of AI models, while AI systems also broaden research opportunities by bringing new perspectives to cognitive processes. This represents a two-way process of development and mutual influence. Such interaction is particularly important in areas where language-based reasoning and interpretation are central. Neuroscience research can also be conducted more easily using AI tools. All of these capabilities can help put significant opportunities at the service of science.

AI applications are widely used across the social, basic, and medical sciences. Among these fields, medical applications and, more specifically, areas such as psychiatry form part of our discussion. In these fields, language, cognition, and meaning play a decisive role. In light of this, careful attention should be paid to the advancement of AI applications in psychiatry. Psychiatric practice and theoretical debates, patient assessment and follow-up, and therapeutic assistance have all benefited from the deployment of AI applications in recent years (7). These developments have been amplified by the coronavirus disease-2019 (COVID-19) pandemic. The demand for mental health treatments was greatly raised by this epidemic, but clinical capacity was similarly constrained. Thus, the relationship between AI and psychiatry underwent a sea change as a result of the epidemic. Access to this service has become even more crucial due to declining interpersonal interactions, rising suicide rates from mental illnesses, social isolation, and increased substance use (8). From a broader perspective, the COVID-19 crisis has increased global interest in AI technologies and accelerated progress across many areas.

The topics briefly summarized above are not independent of each other. On the contrary, they are deeply interconnected. The primary aim of this article is to subject this interconnection to a critical examination as comprehensively as possible. In this context, the article aims to discuss how AI, particularly language-based models, is conceptualized and applied in terms of representation, cognition, and language. Assessing the implications of these developments for medical and psychiatric education is also crucial. First, this analysis will address debates concerning logical and statistical representations in NLP. It will then examine the relationships between AI, linguistics, representation, philosophy, and cognitive models, while also discussing the extent to which AI systems can support or enhance human cognitive functions. Ultimately, framing these discussions within the context of medical and psychiatric practice will enrich the analysis and clarify its clinical relevance. This article will argue that representation, meaning, and context are extremely important in coding human language and other cognitive abilities in AI applications. These applications may be important in producing more efficient and human- like outputs in theoretical and practical fields.

Definitions of AI

First, it is necessary to establish a conceptual framework regarding the definition of AI. Although various definitions of AI have been proposed since the 1950s, it is important to clarify this issue to some extent. AI can be defined in various ways depending on the theoretical and methodological perspective adopted. The literature reflects a wide variety of definitions, consistent with the interdisciplinary nature of this field. Some authors divide these definitions into four main categories: Systems that think like humans, systems that behave like humans, systems that think rationally, and systems that behave rationally (9). We must note from the outset that even these categorizations are insufficient. Since conceptual ambiguity complicates both theoretical discussion and practical evaluation, establishing a clear definition framework should be a primary goal. In this section, three effective approaches to rational action, human- like thinking, and human-like behavior are examined, as they are particularly relevant to discussions concerning cognition, language, and medical practice. These definitions will provide a suitable foundation for subsequent explanations and analyses.

Focused on Rational Action (Logical Approach)

The rational action approach defines AI as systems capable of selecting actions that maximize the probability of achieving predefined goals. Within this framework, intelligence is associated with the ability to make decisions up to a certain level under specific constraints. Of course, this decision-making also progresses through algorithms resembling language and cognitive abilities. A classic example would be a chess program that can evaluate possible moves in advance and select the one with the highest probability of achieving its goals. This approach relies heavily on formal knowledge representation, logical inference, and structured reasoning mechanisms. Here, representation and human-like abilities come into play. Historically, symbolic AI emerged from this tradition and has featured explicit rules and structured representations of knowledge (10). The strengths of this approach include transparency and logical consistency. However, its limitations become apparent in contexts characterized by uncertainty, ambiguity, or incomplete information. Therefore, it is difficult to define tools designed to represent the human mind solely in terms of these formal and rule-based characteristics. It is not even easy to mimic the human mind in depth.

Definition Focused on Thinking Like Humans (Cognitive Approach)

The cognitive approach conceptualizes AI as an attempt to model and replicate certain capacities of the human mind, including learning, reasoning, and problem-solving. This perspective represents one of the most significant intersections between cognitive science and AI research. Rather than focusing solely on observable behavior, it seeks to understand how humans process information and to translate these mechanisms into computational models. NLP systems exemplify this approach by attempting to simulate how humans comprehend, interpret, and generate linguistic responses (11). Although this perspective offers valuable insights into human cognition, accurately modeling complex mental processes remains a substantial scientific challenge. Nevertheless, it has become a highly influential and operationally effective framework within contemporary AI systems.

Definition Focused on Acting Like Humans (Pragmatic Approach)

The pragmatic approach evaluates AI primarily based on observable behavior rather than internal cognitive mechanisms. It should also be noted that this approach is based on linguistic production. According to this view, if a system's responses during interaction are indistinguishable from those of a human, it can be considered intelligent. Alan Turing's Turing Test is the most effective example of this approach and proposes behavioral indistinguishability as a criterion for intelligence (12). Of course, this behavioral similarity is not a motor output- like situation. It focuses on the nature of the written and spoken outputs produced. It can partially answer Turing's famous question. Today's LLMs are increasingly producing more natural and contextually appropriate interactions and therefore fall within the scope of this definition. However, some authors argue that human-like behavior does not necessarily imply true understanding or cognition. In this context, LLMs can produce outputs that simulate human cognitive capacities by utilizing large amounts of data. While producing such outputs, these systems may exhibit forms of expression that closely resemble human actions, but this similarity does not definitively prove the existence of genuine understanding. The development of LLMs is a crucial phase. The process is highly dynamic and fluid. It is not easy to predict where LLMs might evolve.

Representation in AI: Conceptual and Technical Dimensions

If knowledge, along with entities and even emotions belonging to the world, is not transformed into representational objects, it becomes exceedingly difficult to speak of any form of intelligence. Language itself, after all, consists fundamentally of a system of representations. We may now introduce a different perspective by turning to the issue of representation. Addressing representation will help clarify several key domains that will become central in the subsequent analyses.

In fact, the human mind contains a representation of the world. Language itself produces output through symbols and representations. In the context of AI, representation refers to the meaningful and computable encoding of entities, events, or concepts from the real world within an artificial system (13). Similar to how a map selectively represents certain aspects of a city, AI-based representation involves translating the complexity of the world into structured formats that machines can process. This process is not merely technical; it also raises philosophical questions about how meaning is created and interpreted. According to Wittgenstein's later philosophy, meaning is not inherent in symbols but emerges from their use in specific contexts. In his view, "The limits of language are the limits of the world" (14). Consequently, the choice of representational framework directly affects what an AI system can represent, infer, and "understand". Historically, broadly speaking, AI research has yielded three main perspectives on representation.

Symbolic Representation (Symbolic AI)

We have discussed the capacity of language for symbolization and representation. To elaborate further, symbolic representation relies on the encoding of information through clearly defined symbols and formal logical rules. Its philosophical foundations are based on the views of many thinkers and philosophers throughout history. For example, it extends from Leibniz's view of a universal logic language to Boole's logic algebra and Frege's formalization of meaning. This approach has transformed into a different reality with Turing's theory of computation and McCarthy's (15) conceptual explanation of the term AI at the 1956 Dartmouth Conference. Technically, symbolic systems use structures such as production rules, semantic networks, various frame-based representations, and formal logical expressions. They are widely used in expert systems, logical programming, and certain forms of automated theorem proving. Their fundamental strengths are explainability and logical rigor. However, they face significant challenges in dealing with uncertainty, learning from data, and representing nuanced or context- dependent information (16). When context is lacking, an important aspect of reality is missing, and the human dimension awaits completion.

Connectionist Representation (Connectionist AI)

Connective representation positions information not as separate symbolic structures, but as distributed patterns across artificial neural networks. LLMs are largely an advanced combination of these approaches. Many authors have historically contributed to the connectionist representation approach. Among these fundamental contributions are Hebb's (17) relational learning approaches, Rosenblatt's (18) model, and the parallel distributed processing framework developed by Rumelhart and McClelland (19). In connectionist systems, information is encoded in weighted connections between units. Learning in this system occurs through the iterative adjustment of these weights during training. Words that describe objects are converted into semantic concepts and can be represented as high-dimensional vectors associated with multiple features. This paradigm underpins many contemporary applications, including image recognition, speech processing, and NLP systems such as bidirectional encoder representations from transformers (BERT) and generative pre- trained transformers (GPT). Connective models enable generalization and adaptive learning from examples, but their internal representations are often controversial and difficult to interpret (20). These models have quite broad areas of influence in today's world.

Hybrid Representation

Hybrid representation aims to combine the strengths of symbolic and connective approaches while reducing their limitations. Among the first examples of hybrid cognitive architectures are state, operator, and result (21) and adaptive control of thought-rational (22), which combine rule-based reasoning with learning mechanisms. In recent years, this perspective has been revisited in research on neuro-symbolic AI. In such systems, neural components perform perception and pattern recognition tasks, while symbolic components perform explicit reasoning and inference. This effectively combines the other two models. The transformer architecture, one of today's important tools, can also be considered a form of hybrid representation due to its capacity to integrate contextual learning with structured attention mechanisms (23). Hybrid systems offer a promising framework for achieving both high performance and interpretability, particularly in areas requiring reliable reasoning and explainable results. All of these models are used in many AI architectures. These explanations are written to reiterate how important concept representation is in AI models.

AI and Language Models: Technical Evolution and Wittgenstein's Perspective Evolution and Working Mechanisms of Language Models

After briefly summarizing the representation problem, we can now discuss language in general and, more specifically, language models in AI. In doing so, we will try to draw on philosophy a little. We have already made philosophical references here and there since the beginning of the article. However, this article is not based on a discussion of the philosophy of linguistics. But since we are trying to conduct an interdisciplinary discussion here, we will not pass over it without comment.

Until the early 2010s, language modeling in AI tools was primarily based on statistical approaches. N-gram models, which could be considered outdated structures, predicted the probability of a word based on a fixed number of preceding words and could establish language connections in short texts, achieving reasonable success (24). However, these models were insufficient at maintaining semantic consistency in longer texts. In today's evolving world, there is a necessity to generate longer texts and perform complex tasks.

The development of deep learning techniques has been groundbreaking. These developments have greatly simplified tasks in language modeling. RNN and long short-term memory architectures enabled the system to capture sequential dependencies by better propagating information between text steps. Despite these developments, problems remained. Information decay in long sequences remained a problem. This decay kept effectiveness at a certain level in complex linguistic tasks (25). Overcoming this situation seemed inevitable. Human intellect and the technology it produced sought to overcome this as well.

Transformer architectures were subsequently developed. Finally, in 2017, a significant milestone was reached with the introduction of the Transformer architecture. Unlike sequential models, transformers use attention mechanisms that enable the simultaneous evaluation of relationships between all tokens in a sequence. This architectural innovation enabled more comprehensive and contextual modeling, significantly increasing capacity across a wide range of NLP tasks. Models built on this framework, such as OpenAI's GPT, BERT, LaMDA, and PaLM, have been trained on billions of parameters. Thus, LLMs have achieved widespread adoption across a broad range of domains. They perform at a high level not only in word prediction but also in areas such as translation, summarization, question answering, and code generation (4,26). These models have offered significant opportunities in fields such as medicine and psychiatry. AI models have reached this stage after accomplishing challenging tasks such as language execution, representation creation, coding, and information storage.

To elaborate further, typically, these models are trained on large-scale text corpora compiled from various online sources. During pre-training, these models learn linguistic structures through latent language modeling or self-supervised objectives such as subsequent token prediction. Subsequently, fine-tuning on smaller, domain-specific datasets enables adaptation to specialized fields such as medicine and law. This two-stage training process has become a standard method in contemporary NLP research. The system's pre-training and language processing steps have contributed to the development of more useful and effective models.

Wittgenstein and AI Language Models

We briefly mentioned Wittgenstein's ideas in the text. The philosopher's writings can be divided into two periods. What is important for our discussion is his emphasis on the meaning and context of language. We will briefly mention his observations and then try to position them in relation to our topic.

After a certain point, Wittgenstein radically changes his perspective. He no longer argues that language is a perfect logical system, but rather that it is a practical tool used by people in everyday life. His famous slogan is: "Meaning is use". He opposes the idea that language must be a flawless scientific order, because language already works seamlessly in our daily lives. Puzzles and confusion begin when we detach language from its normal use and "take it on vacation". Wittgenstein uses the example of "games" to prove that concepts do not share a single common essence. You cannot find a single feature that encompasses all games such as chess, football, and blind man's buff; however, there are "family resemblances" between them, just like members of a family. This shows that language also does not have a single essence, but consists of many parts (language games) that serve different functions. It clearly demonstrates Wittgenstein's transition from rigid logic to a flexible and practical philosophy of "way of life". Although the idea that "the limits of my language are the limits of my world" is particularly compelling, it later evolved into the notion that "the use of language is the meaning of my world" (14,15,27).

To understand and interpret language-centered approaches in AI, it is necessary to extend Wittgenstein's philosophy of language a little further. We previously discussed the philosopher's early and later thoughts. In his early work, Tractatus Logico-Philosophicus, Wittgenstein argued that language functions as a logical representation of facts in the world. According to this view, propositions derive their meaning from their correspondence with states of affairs, and understanding is based on logical structure (27-32). This perspective assumes that knowledge can be represented through formal symbols and explicit rules, i.e., logical predicates and structured representation systems. Such an approach may offer a more explanatory framework for earlier symbolic AI systems based on formalism. However, it has been shown that such representations are insufficient for modeling the ambiguity, contextual variability, and pragmatic dimensions of natural language (15). Consequently, since language itself is a dynamic, constantly evolving, and context-dependent phenomenon, representation and symbolization alone may not be sufficient to fully grasp the functioning of AI models related to natural language. In general, the philosophy of language should offer a deeper and more nuanced perspective for understanding AI models. Indeed, the Philosopher has revised his views in later periods.

The philosopher abandoned the idea that language is shaped by a single fundamental logical structure in his later work, Philosophical Investigations. Instead, he argued that meaning arises from usage and emphasized the role of context, application, and social interaction. According to this perspective, language functioned as a process of "language games" in which words acquired meaning through their roles in specific activities and ways of life (14). This framework is further clarified by the concept of "family resemblance". In this approach, categories are defined not by fixed essences but by overlapping similarities between specific instances. In other words, meaning and context profoundly shape the dynamic nature of language. While words may appear to carry simple or isolated meanings on their own, within context they constantly transform into lived and situational realities. This approach is a more suitable explanation, particularly for ideal LLMs. It also paves the way for adapting human language abilities to AI models.

Now let's examine some of Wittgenstein's observations in the context of LLMs. Modern LLMs currently in use exhibit clear parallels with the framework expressed in Wittgenstein's later philosophy. Rather than relying on explicit symbolic definitions, LLMs derive meaning from usage patterns within broad linguistic contexts. Their capacity to generate contextually appropriate responses reflects a usage-based representation of language. However, these systems fall somewhat short of fully embodying Wittgenstein's concept of "forms of life". While LLMs can approximate linguistic behaviors, they still lack lived experience, cultural participation, and embodied understanding. Consequently, their linguistic competence remains disconnected from the social and experiential foundations that underpin the human process of meaning creation. These limitations become particularly apparent in fields such as psychotherapy, where context and meaning are deeply intertwined and central to practice. This is because fields like psychotherapy are heavily dependent on both context and the semantic reflections of the world.

Deep Learning, AI, Linguistics, and Cognitive Science

After questioning concepts such as meaning, representation, and context, it becomes possible to turn to the question of human cognition. Ultimately, it is the cognitive capacity of the human mind that produces and sustains these phenomena. Modern Homo sapiens have tremendous capacities related to language, learning, memory, and problem-solving. Perhaps AI will not be able to completely mimic these, but the systems that need to mimic them will be built on these very foundations. The natural course of development may also evolve the direction of progress in different ways. It should be reiterated that examining the relationship between AI architectures and human cognitive mechanisms can contribute both to improving system design and to theoretical insights into the nature of the human mind. However, pursuing this discussion in sufficient depth would exceed the scope of this article.

As previously mentioned, various mechanisms and processes found in deep learning models are crucial in the design of new AI models. Multi-task learning enables artificial systems to acquire multiple competencies simultaneously and transfer knowledge between tasks. Similarly, the human brain can combine visual cues during communication, interpret gestures, and adjust linguistic output according to social context. These abilities are crucial for domains based on human communication. Some researchers suggest that the brain's capacity for parallel and integrative information processing across cognitive domains exemplifies multi-task learning in artificial systems (32). In-depth examination and modeling of the human brain's cognitive production processes can significantly contribute to the further development of AI tools. This relationship is multifaceted: While human cognition influences the design and development of artificial systems, AI can also broaden our understanding of the depth and scope of human cognitive capacity. Furthermore, AI models can make significant contributions to neurophysiological research on the brain.

Applying pre-training and fine-tuning processes to AI models is also quite important. These processes reveal another significant similarity between artificial and human learning processes. While models acquire general linguistic and conceptual knowledge through pre-training on large datasets, fine-tuning enables specialization in specific fields or tasks. This process is similar to how modern humans learn and become specialized in certain fields. Individuals also acquire broad foundational knowledge before specializing in specific areas such as medicine or legal linguistics (33). Initially, knowledge is encoded, contextualized, and learned through representational structures; this acquired knowledge is then applied in various situations. Just as lawyers conclude cases from the knowledge they have previously internalized, LLM systems can also perform domain-related inference operations thanks to this training and architecture.

Humans possess the capacity to learn from extensive sources of information, as well as the ability to acquire new concepts from relatively limited examples, and generally generate solutions to new problems through reasoning rather than relying on extensively stored knowledge. Artificial systems also have the capacity to make broad inferences, at least partially, with a small number of examples and through learning techniques. This process is similar to the working principles of language. Similarly, LLMs have demonstrated the ability to produce appropriate responses to tasks with minimal or no direct training data (34). Despite these advances, semantic fragility remains a significant limitation: LLMs can produce contextually inappropriate or logically inconsistent responses. As previously mentioned, human linguistic understanding relies not only on statistical regularities but also on contextual awareness, intent, cultural knowledge, and concrete experience. At this point, this fundamental limitation becomes evident once again. Further developments may help overcome this problem.

Neurophysiologically, the human mental process is a multifunctional mechanism that brings together phenomena into holistic representations. Meaning emerges through the integration of multiple modalities, including linguistic, visual, auditory, and tactile information. For example, the concept of "cat" is associated not only with a lexical label but also with sensory experiences, behavioral patterns, and lived interactions. Our cat at home is no longer just an ordinary cat. While the concept of a cat requires a certain processing, our cat at home is formed by the involvement of different mental functions in the process. Current AI systems exhibit only a limited capacity for this kind of multimodal integration. However, some artificial neural networks have been shown to develop internal structures resembling grammatical patterns during unsupervised learning and to reflect certain aspects of early human language acquisition (35). Despite these developments, it can be said that this artificial capacity is inferior to the productions of the human mind.

Some studies also continue to argue that human-like language capacity cannot be achieved solely through the use of large amounts of data (36). As highlighted in other content of this article, meaning in human cognition arises from the interaction of intelligent reasoning, contextual interpretation, and experience-based communication. By considering these dimensions together, it can be argued that linguistic theories can play a critical role in enhancing the meaningful capacities of AI outcomes. Including syntactic, meaningful, and pragmatic linguistic reports in the model architectures obtained from AI can help overcome some of the limitations found in purely learning methods.

In general, integrating deep learning into the fields of linguistics and systematics can open up opportunities for efficient and transformative research. Hybrid strategic architectures, multimodal processing, and intelligent storage options embedded in linguistics can make AI models more efficient. At the same time, it enables AI sites to offer more flexible, interpretable, and human-like solutions. In this way, the long-standing goal of creating "machines that can think like humans" can become increasingly achievable.

The Concept of Cognitive Enhancement and AI from a Cognitive Science Perspective

The issue we will look at is how AI models can help improve human thinking skills. This includes things like memory, attention, learning, and making decisions (37). In this case, AI is a major tool for improvement. As mentioned before, some AI learning methods are similar to how humans think. For example, multitasking learning lets artificial systems process many pieces of information at the same time, which is like how the human brain can handle different tasks together (32). Similarly, the pre-training and fine-tuning method is like how people first learn general knowledge before focusing on specific skills (33). After looking at these points, we can ask: can certain AI models also help improve human thinking abilities?

When we ask this question, we realize that even though there are similarities, these methods are only partial copies of human thought, not complete models. This comparison has its challenges. It's possible to improve certain thinking skills and develop certain parts of our cognitive ability using AI tools. However, right now, these capabilities are limited. We can't predict what will happen in the future. Interestingly, some artificial neural networks have shown they can learn language structures similar to grammatical patterns through unsupervised learning. This is like how young children learn language (35). This ability has potential for more development. Using these advances in LLMs models could lead to better results. We could make more sophisticated neural networks.

One of the most effective and widely talked about uses of AI in improving thinking is the human-loop approach. In this model, AI systems support rather than take over thinking. They combine the speed of computers with human judgment and understanding of context. Supporting existing abilities is a more meaningful and lasting goal than replacing them. For example, in clinical decision support systems, AI can find patterns in big datasets while doctors handle the interpretation, ethical evaluation, and final decisions. From a cognitive science point of view, this working together model sees thinking not just as something that happens in the individual mind, but as a process that comes from interactions between people, technology, and the environment.

Transparency and understanding are important for AI to be a useful tool for improving thinking. Explainable AI (XAI) helps build trust, makes things more accountable, and supports better decisions by helping users understand how and why a system makes certain results (38). Without transparency, AI systems might become confusing black boxes, which can harm user trust and make people less willing to accept them ethically. Ethical issues around thinking improvement include becoming too reliant on automated systems, making existing biases worse, and possibly lowering human freedom (39). Handling these risks requires cooperation between technical experts, cognitive scientists, ethicists, and social scientists. When these conditions are met, AI models can greatly help human thinking abilities. This finding fits with the theory of distributed cognition (40,41). Cognitive science brings together knowledge from psychology, linguistics, neuroscience, and AI to model and understand thinking (42).

While some AI methods show aspects of human learning, there are still big gaps in areas like understanding context, emotional intelligence, and cultural meaning, often connected to the idea of "lifestyle" (36). A promising way to fill these gaps is through multimodal processing, which lets systems work with text, images, and sounds. These approaches are more like how humans make sense of meaning and can improve the understanding abilities of AI thinking tools (43). This deeper level of understanding could bring us closer to machines that can think, interpret, and maybe even experience things in ways that are similar to human thinking.

The Use of AI in the Psychiatric Field

Having addressed these conceptual areas, it is appropriate to briefly consider specific application areas. Among the most important of these are psychiatric and psychotherapeutic applications. After examining AI from the perspectives of representation, language, meaning, context, and cognitive enhancement, it becomes necessary to explore its concrete applications within psychiatric practice. Contemporary AI systems used in psychiatry are generally classified as Narrow AI, as opposed to hypothetical forms of Artificial General Intelligence or Super AI (9). These applications are designed to perform specific tasks in well-defined clinical contexts, such as symptom monitoring, risk estimation, or structured therapeutic support. Since our topic is not to discuss more advanced AI models that will be further developed in the future, we will only introduce the subject through existing narrow AI models.

From a methodological standpoint, some authors group AI systems used in psychiatry as symbolic, connectionist, and hybrid approaches. Symbolic systems include rule-based models that operate through pattern matching rather than actual semantic understanding. These include formal logic frameworks, expert systems, and early speech agents such as ELISA. Connectionist approaches encompass deep learning models used for speech analysis, image classification, and text-based prediction, often trained on large clinical or behavioral datasets. Hybrid models integrate symbolic reasoning with neural learning and are particularly valuable in clinical contexts where interpretability and transparency are essential. For example, they can combine rule-based constraints with neural classifiers to support clinical decision-making (3).

AI applications in psychiatry encompass a wide range of fields. Some researchers describe these as NLP-based models, those intertwined with data from assistive devices and digital platforms, often involving passive data collection and longitudinal analysis of language patterns, activity levels, and sleep rhythms to detect depressive symptoms, predict mood swings, and track treatment responses over time (44). Researchers have demonstrated that speech agents such as Woebot and Tess are effective in delivering structured cognitive-behavioral therapy interventions. Randomized controlled trials and clinical evaluations have reported short-term reductions in symptoms of depression and anxiety among young adult users who interact with these tools through text-based dialogue (45). Some practitioners have also used machine learning techniques to identify early indicators of psychosis and schizophrenia. These include studies using automated speech analysis to predict the onset of psychosis in high-risk youth, as well as neuroimaging-based classifiers designed to differentiate clinical groups (46,47). In addition, the same researchers found that avatar-based therapies were effective in improving patients' ability to cope with auditory hallucinations. Randomized clinical trials show that repeated interaction with personalized virtual avatars can reduce the severity of paranoia and increase insight into hallucinatory voices (48). Taken together, these findings and developments appear truly promising.

Beyond diagnostic and therapeutic applications, some researchers have used social support robots like PARO to promote emotional engagement and social interaction in individuals with dementia. Cluster randomized controlled trials have reported improvements in agitation, mood, and social responsiveness during care sessions involving robotic interaction (49). Some clinicians have demonstrated similar effects in pilot studies examining applicability, user acceptance, and short-term mood changes during guided interactions. These clinicians have also shown that robotic applications like eBear are effective in older adults experiencing depressive symptoms (50). Continuous monitoring systems further contribute to psychiatric care by enabling early detection of high-risk behaviors and supporting longitudinal assessment through ongoing data collection.

The advantages of AI in psychiatry include scalability, cost-effectiveness, sustainable accessibility, and improved access to care, particularly in underserved or rural areas. It should also be noted that there are significant limitations in this field. These include a lack of genuine empathy, the emergence of algorithmic bias, risks related to data privacy, and unresolved issues concerning legal and professional accountability. Many authors highlight numerous of these problems in ethical discussions and critical analyses of AI use in healthcare (51,52). We should also point out that detailed and meaningful language use and cultural context are central realities in psychotherapy. Users must carefully design and utilize AI systems to avoid superficial or misleading interactions. Many of the issues we have discussed earlier are most strongly felt in the fields of psychiatry and psychotherapy. While advances in language modeling and contextual representation are expected, the field is still in its early stages of development.

In addition to clinical practice, AI has the potential to support psychiatric research, including large-scale randomized controlled trials. AI-based tools can assist in participant monitoring, data analysis, relapse prediction, and evaluation of treatment outcomes. Recent reviews highlight the role of AI in supporting, rather than transforming, clinical workflows by providing decision support and scalable interventions across a variety of psychiatric conditions (53,54). However, their integration into psychiatric practice must be guided by ethical oversight, clinical judgment, and human-centered care principles. The machines that "think and act like humans", envisioned by many thinkers since Turing's question, and perhaps even much earlier, may one day fully transform into machines that "conduct psychotherapy processes".

Discussion

This article addresses numerous topics. This is because AI is a reality with many dimensions. Most people view AI solely as a technical field of production. However, these tools have much deeper philosophical and intellectual aspects. Narrow perspectives, especially in the context of representation and meaning issues, are now insufficient. This is because these phenomena are the most important reflections of human language. As demonstrated throughout this study, the success of AI systems is directly related not only to computational power or data size, but also to how information is structured, within which representation framework it is produced, and how it is conveyed to the user. Therefore, XAI is not only a technical requirement with a high level of functionality, but also a tool based on knowledge production and suited to human language ability (55). Especially in clinical decision support systems, it is the way the output is justified, rather than the output itself, that generates trust. This trust is also quite important from an ethical point of view.

Repetition is not appropriate, but it seems inevitable to bring the issue together with the problem of representation. The issue of representation occupies a central position here. As some authors have pointed out (56), interpretability means not only internal transparency but also that the decision is contextually understandable. In a clinical context, this requires clearly showing which data patterns the diagnosis recommendation is based on. At this point, the representation problem ceases to be merely a technical modeling issue; it moves into a broader framework concerning the construction of meaning, verifiability, and accountability. New paradigm searches such as quantum computing (57), while having the potential to increase representation capacity, may also make epistemological problems more complex rather than eliminating them. Therefore, the issue is not just more computation, but more qualified meaning production. Because the human mind is not a purely computational structure. Meaning is a reality constructed by this structure through language. In this respect, it again becomes the subject of philosophical debates.

The evolution of language models concretizes this debate. With the Transformer architecture, the capacity for capturing contextual patterns has increased significantly (23). However, this development also evokes a theoretical shift from Wittgenstein's early logical design understanding to his later "language games" approach (14). Modern LLMs can generate meaning from usage patterns to a limited extent; however, they still do not possess a "way of life". This is because they cannot fully represent the mind of a living human being. Above all, the question "Can machines really produce emotions?" remains unanswered. Who knows, perhaps one day AI models capable of feeling will be developed. For example, in fields such as psychiatry, meaning arises not only from word sequences but also from experience, culture, emotion, and contextual interaction. Therefore, the gap between technical progress and phenomenological experience persists. This situation seems likely to continue for quite some time.

The role of neuro-symbolic approaches in bridging this gap cannot be denied (30). Instead of purely statistical learning, the integration of logical inference and explicit representation layers can increase reliability, particularly in high-risk decision-making areas. The involvement of symbolic structures can contribute to making model outputs more consistent with clinical reasoning. However, this raises a new problem: Excessive formalization and algorithmization can diminish the flexibility of human communication. Therefore, the fundamental question for future research is how to establish a balanced structure between performance and depth of meaning.

Comparing linguistic models with neural networks is also important in this context. The differences between dependency parsers and neural disambiguation systems (58) demonstrate the extent to which artificial systems internalize the relationship between syntactic structure and semantic interpretation. The integration of structured lexical resources such as VerbNet (59) can increase contextual depth; however, the cultural layering of human language is still not fully represented. As mentioned earlier, all tools are still far from ideal. At this point, multimodality offers a new perspective. EEG-based language processing findings (60) and studies focusing particularly on the N400 component (61) demonstrate how the human brain processes semantic incongruity. Barsalou's embedded cognition approach (62) proposes that meaning is not solely linguistic but is also connected to bodily and action-based experience. Representations developed based on this approach could yield more reliable results, particularly in psychiatric applications. This is because psychiatric assessment requires not only verbal expression analysis but also the interpretation of tone, gestures, timing, and emotional context. The interpretation of bodily signals, in particular, is essential for social beings. Reading facial expressions, such as signs that appear when lying, is also important. Perhaps multimodal- neurobiological approaches can make significant contributions to the development of new AI models.

AI applications in psychiatry offer significant opportunities in response to growing demand (7,63). The need for accessibility has become more apparent in the post-pandemic period. However, it is clear that these tools should not replace human contact but rather support it. The real potential for transformation lies in the "cognitive partnership" model rather than "replacement". AI can support clinicians with its pattern recognition and data analysis capabilities; however, interpretation, ethical evaluation, and responsibility must remain the domain of human judgment.

The new perspective emerging from this study is as follows: The relationship between AI and fields such as psychiatry is not merely a matter of technological development; this relationship concerns how representation theories translate into clinical meaning production. In other words, the real issue is not "how accurate are AI predictions?" but rather "how well do the representations it produces align with clinical meaning?" Future research must evaluate the phenomenological adequacy of representations as well as performance metrics.

In conclusion, AI shows promise in fields such as psychiatric applications and psychotherapy; however, full utilization does not seem possible without resolving issues of representation, context, empathy, and explainability. Interdisciplinary collaboration, neuro-symbolic architectures, multimodal representations, and ethical frameworks will be key determinants of this process. The claim to model the human mind requires not only technical progress but also a deeper questioning of the nature of meaning.

Footnotes

Authorship Contributions

Surgical and Medical Practices: A.R.T., Concept: F.B., A.R.T., Design: F.B., A.R.T., Data Collection or Processing: F.B., A.R.T., Analysis or Interpretation: F.B., A.R.T., Literature Search: F.B., A.R.T., Writing: F.B., A.R.T.

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