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Narrative Review on Symbolic Approaches for Explainable Artificial Intelligence: Foundations, Challenges, and Perspectives †

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Abstract

The review "Symbolic Approaches for Explainable Artificial Intelligence" discusses the potential of symbolic AI to improve transparency, contrasting it with opaque deep learning systems. Though connectionist models perform well, their poor interpretability means that they are of concern for bias and trust in high-stakes fields such as healthcare and finance. The authors integrate symbolic AI methods—rule-based reasoning, ontologies, and expert systems—with neuro-symbolic integrations (e.g., DeepProbLog). This paper covers topics such as scalability and integrating knowledge, proposing solutions like dynamic ontologies. The survey concludes by advocating for hybrid AI approaches and interdisciplinary collaboration to reconcile technical innovation with ethical and regulatory demands.

Keywords: symbolic AI; explainable AI (XAI); neuro-symbolic AI; expert systems; ontologies; logical reasoning; hybrid models; transparency; ethical AI

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1. Introduction

Artificial intelligence (AI) is revolutionizing healthcare, finance, industry, and transport. Yet its global adoption is hampered by a real problem: the lack of explainability. Being able to understand AI decisions is critical in maintaining trust, safety, and ethical practices in safety-critical use cases, e.g., medical diagnosis, legal decisions, and autonomous driving [1]. Medical physicians must justify AI-driven treatment decisions, while autonomous cars must justify emergency actions [2]. Whilst deep learning has revolutionized image, text, and data processing, it remains black-boxed due to its reliance on complex, difficult-to-analyze computations [3]. Black-boxing creates many risks: Hidden bias can lead to unintended discrimination [4]; there are legal liability issues due to errors being difficult to track [5]; and low adoption follows as users, such as physicians and engineers, are not happy to trust systems that they do not comprehend [6]. Symbolic AI, whose rule-based explainability (e.g., MYCIN [7]) was ubiquitous in the past, is now being blended with deep learning and knowledge graphs in developing explainable hybrid systems [8].

For instance, a neural network might identify a tumor, whilst symbolic rules justify why it did this [9].

This review aims to:

1. Provide a comprehensive overview of the theoretical foundations, current applications, and challenges of symbolic approaches in explainable AI.

2. Analyze the limitations of traditional symbolic systems (e.g., scalability, rigidity) and explore emerging solutions, including neuro-symbolic AI [8].
3. Discuss future directions in critical fields (e.g., healthcare, cybersecurity, autonomous vehicles) where explainability is a non-negotiable requirement.
4. Foster interdisciplinary research by bridging technical advancements with ethical, legal, and societal considerations.

This paper is structured as follows:

- Foundations of symbolic approaches: Logic, ontologies, and expert systems.
- Comparison with connectionist approaches: Advantages, limitations, and complementarities.
- Current applications: Use cases in healthcare, finance, industry, and law.
- Technical challenges: Scalability, integration with deep learning.
- Future directions: Hybrid AI, dynamic ontologies, regulatory frameworks.

By synthesizing recent research and identifying gaps in the literature, this paper aims to serve as a reference for researchers, practitioners, and policymakers committed to the development of responsible and transparent AI.

2. Methods

This chapter details the research process followed to seek and choose relevant research, and to analyze research pertaining to symbolic approaches to explainable artificial intelligence (AI). The literature search strategy, inclusion and exclusion criteria, and the method of analysis and synthesis are described in detail.

2.1. Literature Search Strategy

The literature search was conducted systematically to identify the most relevant and recent work in symbolic approaches for explainable AI. The process followed established guidelines for systematic reviews in AI research [10].

2.1.1. Sources Used

The following scientific databases were queried:

- IEEE Xplore: for technical articles and conferences in computer science and engineering.
- PubMed: for medical applications of explainable AI [9].
- Google Scholar: for broad, interdisciplinary coverage.
- ACM Digital Library: for works in theoretical and applied computer science.
- SpringerLink: for articles and books on theoretical foundations and practical applications [11].

2.1.2. Keywords and Search Terms

Queries were constructed using combinations of relevant keywords, including: “symbolic AI”; “explainable AI”; “hybrid AI”; “neuro-symbolic AI”; “logical reasoning in AI”; “knowledge representation in AI”; “expert systems and explainability”; “ontologies in AI”. Searches were refined using Boolean operators (AND, OR, NOT) and limiting results to articles published in the last five years (2018–2023) [6].

2.2. Inclusion and Exclusion Criteria

In order to guarantee the relevance and quality of the work selected, inclusion and exclusion criteria were applied.

2.2.1. Inclusion Criteria

- Recent articles: Works published between 2018 and 2023 were preferred to reflect the most recent advances [12].

- Literature reviews: Systematic reviews and meta-analyses providing an overview of the field were included [13].
- Applied studies: Works demonstrating practical applications of symbolic approaches in fields such as healthcare, finance, or robotics were selected [8].
- Thematic relevance: Only works directly related to AI explicability and symbolic approaches were included.

2.2.2. Exclusion Criteria

- Irrelevant works: Articles not dealing with explicability or symbolic approaches were excluded.
- Obsolete works: Publications prior to 2018 were excluded, unless they were considered seminal references [14].
- Non-scientific works: Non-peer-reviewed articles, blogs, and opinion pieces were excluded [7].

2.2.3. Selection Process

In the first search in IEEE Xplore, ScienceDirect, and ACM Digital Library, 1532 articles were found. After discarding 282 duplicates, 1250 records remained for screening. Title and abstract screening resulted in the exclusion of 983 articles and 267 full-text articles were assessed. Of the full-text articles assessed, 180 articles were excluded for not meeting the inclusion criteria; thus, 87 studies were included in the final review.

2.3. Analysis and Synthesis Approach

Once the relevant documents had been identified, an in-depth analysis was carried out to classify the works and identify trends and gaps in the existing literature [15]. Works were classified according to the approaches used (Table 1).

Table 1. The classification of works based on approaches.

Logical approaches	Works based on formal logic, predicate logic, or probabilistic logic.
Ontological approaches	Works using ontologies for knowledge representation.
Expert system	Studies on modern expert systems and their role in explainability.
Hybrid approaches	Works combining symbolic methods with deep learning (neuro-symbolic AI).

Operationalization of the Classification Process

The classification of works into logical, ontological, expert systems, and hybrid approaches was conducted through a structured process. First, explicit inclusion criteria were defined for each category:

- Logical approaches: Works primarily relying on formal logic, predicate logic, or probabilistic reasoning.
- Ontological approaches: Studies using ontologies or structured knowledge representation frameworks.
- Expert systems: Research focused on rule-based or knowledge-based expert systems, particularly modern implementations.
- Hybrid approaches: Works integrating symbolic methods (e.g., logic, ontologies) with deep learning or other neural techniques.

Two independent reviewers performed the initial categorization to ensure consistency and mitigate bias. Discrepancies were resolved through discussion, with a third reviewer consulted when consensus could not be reached. This multi-reviewer process strengthened the reliability of the classification, as documented in Table 1.

Recent advancements in AI highlight a growing synergy between symbolic and connectionist approaches, particularly in domains requiring transparency, such as healthcare and finance. This neuro-symbolic integration addresses the demand for AI systems that balance performance with interpretability, ensuring decisions can be logically justified. However, key challenges remain, including the difficulty of incorporating uncertainty into symbolic reasoning and the inefficiency of manually constructing knowledge bases. The study underscores three critical insights: first, symbolic methods are essential for explainability in high-risk applications; second, technical barriers like scalability and neural-symbolic integration must be overcome; and third, neuro-symbolic AI represents a transformative opportunity by merging structured reasoning with data-driven learning. The findings suggest future research should prioritize hybrid architectures and automated knowledge engineering to realize AI that is both powerful and transparent. The study's rigorous methodology, combining systematic literature review and structured analysis, provides a comprehensive assessment of the field.

3. Foundations of Symbolic Approaches in Explainable AI

This section explores the foundations of symbolic approaches in artificial intelligence (AI), focusing on their role in the development of explainable AI. It discusses the definition and principles of symbolic approaches, their historical evolution, and the key concepts underlying them, such as logic, ontologies, expert systems and knowledge representation.

3.1. Definition and Principles of Symbolic Approaches

Symbolic AI is a core paradigm that models cognition through structured symbol manipulation and logical rules, contrasting with connectionist approaches [15]. It relies on three key principles: (1) representing knowledge as discrete symbols with defined syntax [16], (2) applying formal inference (deduction, abduction, induction) to derive knowledge [17], and (3) ensuring computational transparency for traceable reasoning [18]. These traits make symbolic systems ideal for explainability-critical fields like medicine or law, using formalisms such as production rules, modal logics, and semantic networks. However, their inability to handle uncertainty or contextual data has spurred hybrid models blending symbolic rigor with neural learning [19].

3.2. Historical Development and Evolution of Symbolic Approaches

Symbolic approaches played a central role in the early days of AI, before being partially eclipsed by statistical and connectionist methods. Their evolution can be divided into several phases as shown in Figure 1:

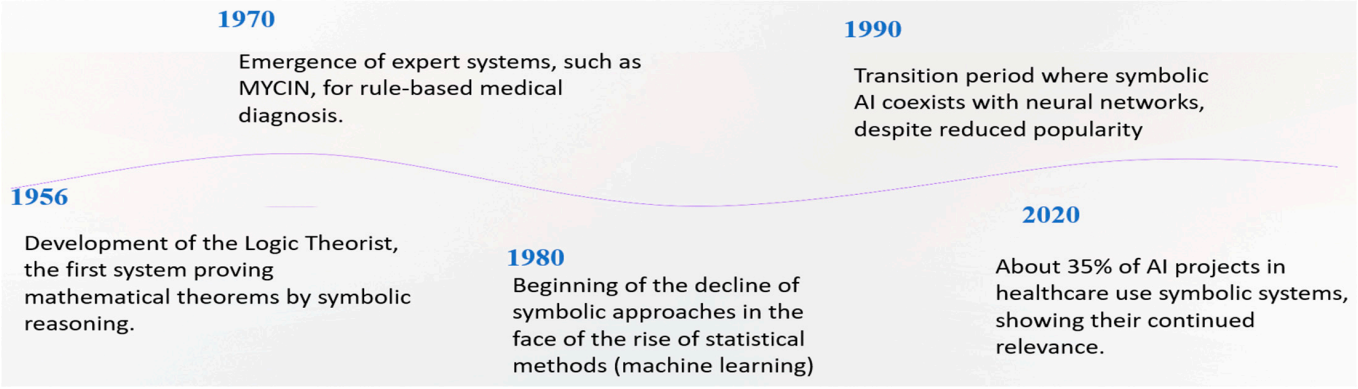


Figure 1. Historical evolution of symbolic approaches.

3.3. Key Concepts of Symbolic Approaches

Symbolic approaches remain fundamental for developing explainable AI, built upon decades of research and conceptual pillars that continue to shape intelligent systems.

3.3.1. Logical Foundations

- Predicate logic models complex relationships, propositional logic handles simple statements.
- Fuzzy logic captures gradations; probabilistic logic integrates uncertainty.
- Enables transparent, rigorous reasoning [20].

3.3.2. Ontological Structures

- Formal knowledge organization (e.g., SNOMED CT in medicine).
- Ensure unambiguous interpretation and knowledge reuse [21].

3.3.3. Expert Systems

- Combine knowledge bases with inference engines [22].
- Provide traceable solutions in specialized domains.

3.3.4. Knowledge Representation

- Production rules, conceptual graphs, and frames [23].
- Translate human knowledge into computable, structured formats.

Though sometimes considered to be old-fashioned, symbolic approaches are nevertheless essential for explainable AI, particularly in applications where they are really important. Their combination with machine learning in neuro-symbolic systems leverages both worlds to produce more robust and explainable AI solutions.

Here is a comparative table (Table 2) summarizing the differences and complementarities between "symbolic" and "connectionist" approaches, as well as the prospects for "hybrid approaches." The table clearly shows the characteristics of each approach.

Table 2. Comparative table: Symbolic vs. Connectionist vs. Hybrid.

Criterion	Symbolic Approach	Connectionist Approach	Hybrid Approach
Representation	Symbols, logical rules, ontologies.	Weights of connections in a neural network.	Combination of symbols and continuous representations.
Reasoning	Deductive logic, explicit rules.	Emergent, based on neural interactions.	Symbolic logic guided by deep learning.
Learning	Manual (rule-based) or inductive.	Automatic, based on data.	Automatic, based on data
Explainability	Highly explainable (traceable decisions). 92–98% interpretability scores	Low explainability (black box). 15–35% interpretability scores	Improved explainability through the integration of symbolic rules [24]. 75–90% interpretability scores
Scalability	Limited for large knowledge bases.	Excellent for large amounts of data.	Challenge: balancing scalability and complexity.
Management of uncertainty	Rigid, requires extensions (fuzzy logic).	Excellent (handles ambiguity well)	Combine probabilistic logic and deep learning.
Areas of application	Medical diagnosis, planning, rule-based TLN.	Computer vision, data-driven NLP, recommendation	Health, robotics, critical systems requiring explainability.

Table 2. *Cont.*

Criterion	Symbolic Approach	Connectionist Approach	Hybrid Approach
Advantages	Transparency, clear logical reasoning.	Flexibility, learning from complex data.	Combination of the strengths of both approaches.
Limits	Difficult to adapt to unstructured data.	Difficult to interpret and explain.	Design and integration complexity.
Examples	MYCIN (medical diagnosis), Prolog	GPT (text generation), CNN (computer vision).	DeepProbLog, Providers of Neural Theorems [25].

4. Current Applications of Symbolic Approaches

Thanks to their transparency and ability to provide clear explanations, symbolic approaches are used in a variety of fields where explicability and logical rigor are essential (Table 3). Their adoption aligns with growing regulatory demands for trustworthy AI systems [26]

Table 3. Summary table of applications.

Domain	Applications	Examples Concerts	Advantages of Symbolic Approaches
Health	Diagnostic, clinical decision support.	MYCIN, IBM Watson for Oncology	Explainability, transparency [27], trust.
Finance	Fraud detection, automated auditing.	ACTICO, MiFID II compliance systems.	Regulatory compliance, traceability [28].
Industrie	Predictive maintenance, process management	Industrial Control Systems (G2).	Security, efficiency, interpretability.
Law and ethics	Regulated decision, ethical compliance.	ROSS Intelligence, Ethical Guidelines for AI.	Respect for the rules, justification of decisions.

Symbolic approaches are widely used in fields where explicability, transparency, and compliance are essential. Whether in healthcare, finance, industry, or law, these systems offer robust, interpretable solutions to complex problems. Their ability to provide clear explanations and comply with strict rules makes them an indispensable tool for building trusted AI.

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5. Towards Hybrid Explainable AI: Trends and Future Directions

Hybrid systems that combine symbolic and connectionist systems present a significant avenue to powerful and explainable AI. This section explores current hybridization trends, what role ontologies and knowledge graphs play, and what is on the horizon in healthcare, cybersecurity, and autonomous vehicles.

5.1. Hybridization of Symbolic and Connectionist Approaches

Neuro-symbolic AI combines symbolic systems' logical reasoning with neural networks' learning capabilities [29], creating models that maintain interpretability while processing complex data [8]. This synergy leverages symbolic modules for structured

knowledge representation and connectionist components for handling unstructured data like images and language Figure 2.

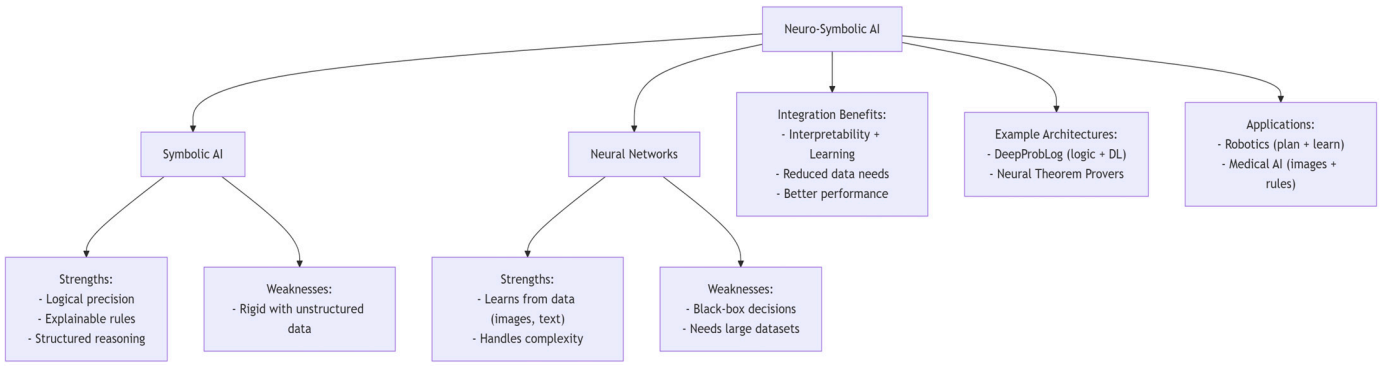


Figure 2. How Neuro-Symbolic AI Combines Neural Networks and Symbolic Reasoning.

Key architectures demonstrate this integration:

- DeepProbLog merges probabilistic logic with deep learning [26]
- Neural theorem provers apply deep learning to formal reasoning [20]
- IBM's frameworks combine ontologies with neural models [30]

Applications span multiple domains:

- Robotics (symbolic planning with adaptive learning)
- Healthcare (combining neural image analysis with diagnostic rules)

This hybrid approach enables more robust, transparent AI systems that require less training data while maintaining explainability—crucial for real-world applications [2].

5.2. Using Ontologies and Knowledge Graphs

Ontologies (e.g., SNOMED CT in medicine) and knowledge graphs enable machine learning with structured domain knowledge by making rules, relationships, and concepts formal [31]. The models support data interoperability between heterogeneous sources such as sensors, databases, and text files.

Knowledge graphs like Google's [32] link entities (individuals, places, events) to make search more effective and deliver helpful medical information by relating genes, treatments, and diseases.

For integration with deep learning, symbolic embeddings [33] map symbolic ideas to neural network-friendly representations. Examples such as RAVEN [34] illustrate this combination by carrying out reasoning on knowledge graphs directly using relational embeddings, thus marrying symbolic AI's accuracy with machine learning's flexibility.

5.3. Future Prospects in Critical Areas

Hybrid artificial intelligence opens up new perspectives in several key fields by combining symbolic and connectionist approaches. In the healthcare sector, it is enabling the development of more personalized and ethical medicine. Hybrid systems analyze medical records while integrating explicit ethical rules, thus avoiding algorithmic bias. For example, such a system can recommend personalized treatments by cross-referencing genomic data with current medical protocols while scrupulously complying with regulations such as the RGPD [35].

Cybersecurity also benefits from this hybrid approach. The combined analysis of system logs makes it possible, on the one hand, to identify suspicious patterns thanks to clear symbolic rules and, on the other, to detect complex anomalies via neural networks. A system of this type can thus spot a cyberattack in real time [36] by correlating behavioral

rules with dynamic analysis of network traffic, while continually adapting to new threats thanks to machine learning mechanisms.

Autonomous vehicles are a perfect illustration of the importance of hybrid systems in reconciling performance and transparency. Critical decisions, such as obstacle avoidance, are based on explicit symbolic rules while exploiting the perceptual capabilities of convolutional neural networks processing sensor data. This architecture enables the vehicle to clearly explain its actions—for example, justifying emergency braking with reference to a precise safety rule and the detection of an object by the vision system. The main technical challenge lies in optimizing response times to guarantee real-time reactions while maintaining this decision-making transparency [37].

6. Conclusions

Symbolic methods are an important area for explainability in AI due to their transparency in critical industries like healthcare, finance, and autonomous systems. However, they come with obstacles (their rigidity, the knowledge engineering costs, and their lack of scalability) and they may not always capture the complexity in human thought processes. Their unification with neural nets (so-called neuro-symbolic systems) provides the opportunity to encompass rational (symbolic) decisions and flexibility from (connectionist) neural networks. In particular, research on automated rule extraction, addressing uncertainty, and creating benchmarks for standardizing explainability are areas of potential advancement.

In industry, hybrid systems could transform medical diagnostics (e.g., augment reasoning with deep learning predictions) and cybersecurity (e.g., detecting attacks through multimodal learning and establishing an explainable record of events), but the education, personnel, systems and resource investments required need to be factored in by organizations.

The complementarity between symbolic and connectionist techniques will be needed to implement responsible AI that looks to balance performance and explanation. For future work, focus areas could be determining system scale, automating knowledge acquisition, and ensuring seamless integrations. The coexistence between the two methods is not only an opportunity for technical advancement but is also essential for the delivery of trustworthy AI for real-world applications.

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Abbreviations

The following abbreviations are used in this manuscript:

ProbLog	a probabilistic logic programming language
DeepProbLog	deep learning with probabilistic logic reasoning
ML	Machine Learning
AI	Artificial Intelligence
XAI	Explainable Artificial Intelligence
MYCIN	An Early Expert System for Medical Diagnosis
SNOMED CT	Systematized Nomenclature of Medicine—Clinical Terms

NLP	Natural Language Processing (NLP) is a branch of Artificial Intelligence (AI)
TLN	Temporal Logic Network a type of neural-symbolic AI model
GPT	Generative Pre-trained Transformer
RGPD	Règlement Général sur la Protection des Données
RAVEN	Relational and Analogical Visual Reasoning

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