Al-Farouk journal of sciences
Volume (2), Issue (1) (March, 2026)
ISSN: 3135-2359

مجلة الفاروق للعلوم
المجلد (2) العدد 1 مارس 2026
ردمد: 3135-2359

Foundations of Artificial Intelligence: Transitioning from Symbolic Reasoning to Data-Driven Intelligence

TIBRAH ALMABROUK MOHAMED ALRAJHI

Higher institute for sciences and technology – regdaleen

tbra.rajh@histr.edu.ly

تاريخ الاستلام: 2026/01/06 تاريخ المراجعة 15 / 2 / 2026 تاريخ القبول: 2026/03/08- تاريخ النشر: 03/15/ 2026

Abstract

Artificial Intelligence (AI) has undergone a remarkable transformation, evolving from symbolic reasoning systems to data-driven machine intelligence. Early AI systems relied on explicit rule-based knowledge representations that were transparent, logical, and interpretable. However, they lacked adaptability, scalability, and learning capability. The emergence of machine learning enabled AI systems to identify patterns from data and improve performance through experience rather than depending solely on expert-defined rules. This transition was further accelerated by artificial neural networks and deep learning, which leverage large-scale data and computational power to learn complex representations that often outperform manually engineered features. This paper presents a comparative analysis of the principal paradigms of artificial intelligence: Symbolic AI, Machine Learning, and Deep Learning, based on explain ability, scalability, data dependency, and suitability for real-world applications. In addition, a conceptual Hybrid AI framework is proposed to integrate reasoning and learning in a unified architecture that balances performance with interpretability. The study aims to support researchers and practitioners in selecting suitable AI paradigms for modern intelligent systems and highlights the growing importance of explainable, reliable, and human-centered AI.

Keywords: Artificial Intelligence, Symbolic Reasoning, Machine Learning, Deep Learning, Hybrid AI, Explainable AI

الملخص

لقد شهد الذكاء الاصطناعي (AI) تحولًا كبيرًا، حيث انتقل من أنظمة الاستدلال الرمزي إلى الذكاء المعتمد على البيانات. اعتمدت أنظمة الذكاء الاصطناعي المبكرة على تمثيلات معرفية صريحة قائمة على القواعد، وكانت هذه الأنظمة تتسم بالوضوح والمنطقية وقابلية التفسير. ومع ذلك، فقد افتقرت إلى القدرة على التكيف، وقابلية التوسع، وإمكانية التعلم. وقد أتاح ظهور تعلم الآلة لأنظمة الذكاء الاصطناعي إمكانية التعرف على الأنماط من البيانات وتحسين الأداء من خلال الخبرة، بدلًا من الاعتماد فقط على القواعد التي يضعها الخبراء. وتسارع هذا التحول بشكل أكبر مع ظهور الشبكات العصبية الاصطناعية والتعلم العميق، اللذين يعتمدان على البيانات واسعة النطاق والقدرة الحاسوبية لتعلم تمثيلات معقدة غالبًا ما تتفوق على السمات المصممة يدويًا.

تقدم هذه الورقة تحليلًا مقارنًا للنماذج الرئيسة في الذكاء الاصطناعي، وهي :الذكاء الاصطناعي الرمزي، وتعلم الآلة، والتعلم العميق، وذلك استنادًا إلى قابلية التفسير، وقابلية التوسع، والاعتماد على البيانات، والملاءمة للتطبيقات الواقعية .بالإضافة إلى ذلك، يتم اقتراح إطار مفاهيمي للذكاء الاصطناعي الهجين يهدف إلى دمج الاستدلال والتعلم ضمن بنية موحدة تحقق التوازن بين الأداء وقابلية التفسير.

وتهدف الدراسة إلى دعم الباحثين والممارسين في اختيار النماذج المناسبة للذكاء الاصطناعي في الأنظمة الذكية الحديثة، كما تسلط الضوء على الأهمية المتزايدة للذكاء الاصطناعي القابل للتفسير، والموثوق، والمتمحور حول الإنسان.

الكلمات المفتاحية :الذكاء الاصطناعي، الاستدلال الرمزي، التعلم الآلي، التعلم العميق، الذكاء الاصطناعي الهجين، الذكاء الاصطناعي القابل للتفسير.

I. Introduction

Artificial Intelligence (AI) has emerged as a pivotal technology enabling advancements in science, business, and society. This is attributable to enhancements in data accessibility, processing capacity, and learning algorithms. Modern AI systems are increasingly reliant on data-driven approaches, particularly machine learning and deep learning, which have demonstrated remarkable effectiveness in areas such as computer vision, natural language processing, and decision support (LeCun, Bengio, & Hinton, 2015; Goodfellow, Bengio, & Courville, 2016). Despite the efficacy of these models, purely data-driven approaches frequently encounter challenges related to interpretability, data requirements, and susceptibility to bias, which raises concerns in domains where safety is paramount and regulations are stringent (Doshi-Velez & Kim, 2017; Rudin, 2019). These issues have heightened public interest in explainable and reliable AI, which must be transparent, robust, and supervised by humans (DARPA, 2017; IEEE, 2019). Recent research demonstrate that no single AI standard is sufficient for all issue settings. Deep learning excels in perception and representation, although symbolic reasoning remains valuable for logic, constraints, and comprehensible decision-making processes (Marcus, 2018; Pearl & Mackenzie, 2018). Consequently, hybrid AI approaches that integrate learning-based models with symbolic reasoning have emerged as a viable means to develop AI systems that are both efficient and comprehensible (Bengio, Lecun, & Hinton, 2021; Kautz et al., 2021).

This study presents a concise comparative examination of key AI paradigms and develops a hybrid conceptual framework that enables adaptive learning while ensuring explainability. The objective is to provide individuals with practical guidance on selecting and designing AI systems that will function effectively in contemporary real-world applications.

II. Contributions

This paper makes the following contributions:

1. It presents a **historical and theoretical overview** of the evolution of artificial intelligence paradigms.
2. It provides a **comparative analysis** of Symbolic AI, Machine Learning, Deep Learning, and Hybrid AI.
3. It proposes a **conceptual Hybrid AI framework** that combines perception, learning, and symbolic reasoning.
4. It offers **practical guidance** for selecting AI methodologies based on problem characteristics and application requirements.
5. It highlights the importance of **explainability, reliability, and human-centered AI** in modern intelligent systems.

III. Review of literature

In recent years, data-driven methods, particularly deep learning, have become the dominant paradigm in artificial intelligence research and applications. These approaches have achieved exceptional performance across a wide range of tasks, including image classification, object detection (Alrawayati and Tökeşer, 2021), speech recognition, and language understanding. Advances in convolutional neural networks and transformer-based architectures have significantly improved representation learning and perceptual intelligence (LeCun et al., 2015; Vaswani et al., 2017). However, despite their success, many studies have shown that deep learning systems suffer from important limitations. These include limited interpretability, sensitivity to adversarial or out-of-distribution inputs, high dependence on labeled data, and challenges in causal reasoning and generalization (Rudin, 2019; Recht et al., 2019; (Alrawayati and Tökeşer, 2021); Alrawayati and Ümit Tokeşer. 2025). Such limitations are especially problematic in safety-critical and regulated domains, where AI systems must provide justifiable and trustworthy decisions.

To address these concerns, Explainable Artificial Intelligence (XAI) has emerged as an important area of research focused on improving the transparency and interpretability of AI models. Existing literature emphasizes the need for models that are inherently interpretable rather than relying solely on post-hoc explanation techniques, especially in high-stakes applications (Doshi-Velez & Kim, 2017; Gunning & Aha, 2019; Holzinger, 2022). Parallel to the development of XAI, there has been renewed interest in integrating symbolic reasoning with learning-based models. Neuro-symbolic and hybrid AI approaches aim to combine the generalization power of neural networks with the structure, logic, and interpretability of symbolic systems (Marcus, 2018; Kautz et al., 2021). Recent studies argue that such integration is essential for achieving stronger reasoning, causal understanding, and more robust forms of intelligence (Pearl & Mackenzie, 2018; Bengio et al., 2021; Dalla, 2020).

Overall, the literature suggests that the future of AI is unlikely to rely on a single dominant paradigm. Instead, hybrid approaches that combine data-driven learning with symbolic reasoning are increasingly viewed as a promising direction for building AI systems that are both effective and understandable. This paper contributes to this emerging perspective by offering a comparative analysis and a conceptual framework aligned with current research trends.

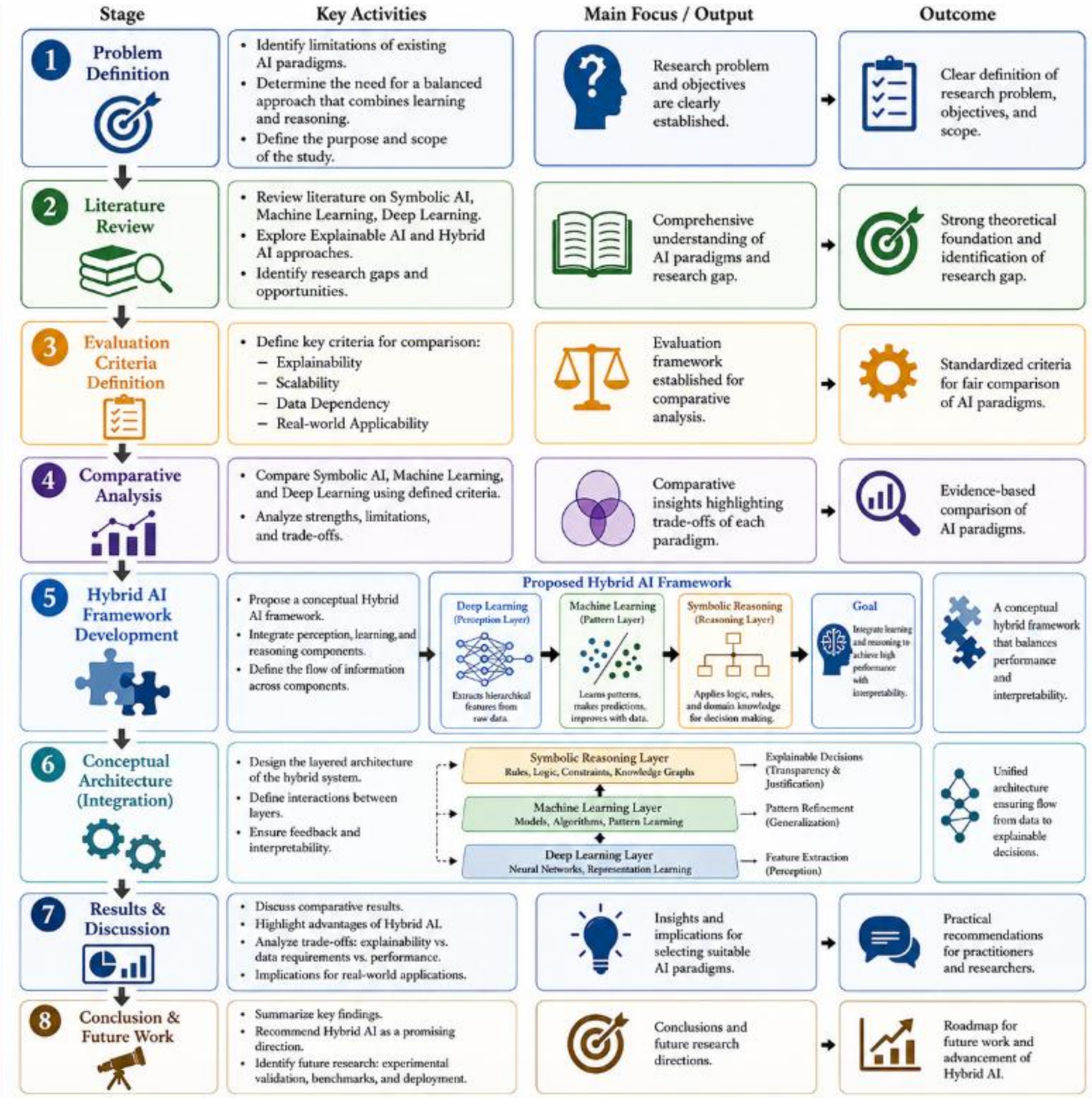

Figure. 1 The research methodology diagram

IV. Foundations of Artificial Intelligence Paradigms

A. Symbolic AI

Symbolic AI, often referred to as Good Old-Fashioned AI (GOFAI), is based on explicit rules, logic, and structured knowledge representation. In this paradigm, intelligence is modeled through symbols and formal reasoning processes such as inference, search, and rule application (Keles et al., 2024); (Gergerli et al., 2023). Symbolic AI is highly interpretable because the reasoning steps can be traced and explained. It is particularly effective in domains with clearly defined rules, such as expert systems, theorem proving, and decision support. However, symbolic AI has significant limitations. It depends heavily on manually encoded knowledge, which is difficult to scale and maintain in complex or dynamic environments (Keles et al., 2024). It also struggles with uncertainty, noisy data, and tasks involving perception such as image or speech recognition.

B. Machine Learning

Machine Learning (ML) shifted AI toward a data-driven paradigm by enabling systems to learn patterns from examples rather than relying solely on predefined rules. ML methods such as regression, decision trees, support vector machines (Ben Dalla et al., 2026), and ensemble learning have been widely used in classification, prediction, clustering, and recommendation tasks. Compared with symbolic AI, machine learning offers greater adaptability and can improve performance through exposure to data (Ben Dalla et al., 2026). However, many ML models still require substantial feature engineering and may sacrifice transparency depending on the algorithm used. While some models such as decision trees remain interpretable, others operate as semi-transparent statistical approximators.

C. Deep Learning

As shown in Table I, which compares different types of artificial intelligence, deep learning (DL) represents a major advancement within machine learning and is based on artificial neural networks with multiple hidden layers Elghaffi et al., (2026). These models automatically learn hierarchical representations from raw data, making them highly effective for complex tasks such as image recognition, natural language understanding, and speech processing (Kale et al., 2024). Deep learning has achieved state-of-the-art performance in many domains because of its ability to extract high-level features directly from large datasets (Keles et al., 2024); (Gergerli et al., 2023); (Ben Dalla et al., 2026). Nevertheless, these systems often function as "black boxes," making their decisions difficult to interpret. They also require significant amounts of data, computational resources, and training time, which can limit their practicality in some contexts (Ben Dalla et al., 2024).

Table I. A comparison of different types of artificial intelligence

Paradigm	Explainability	Scalability	Data Requirement
Symbolic AI	High	Low	Low
Machine Learning	Medium	Medium	Medium
Deep Learning	Low	High	Very High
Hybrid AI	High	High	Medium–High

D. Hybrid AI

Hybrid AI combines symbolic reasoning with machine learning and deep learning techniques in order to exploit the strengths of each paradigm. In such systems, neural or statistical models can handle perception and pattern recognition, while symbolic components can enforce logic, domain constraints, and interpretable reasoning (Çakır et al., 2022); (Sinecen et al., 2009); (Yumus et al., 2020). Hybrid AI is increasingly recognized as a promising direction for future intelligent systems because it offers a balance between adaptability, performance, and explainability. It is particularly suitable for applications that require both data-driven intelligence and human-understandable decision-making (Dalla and Ahmad, 2023); (Tokgöz et al., 2024); (Karal and Dalla, 2025).

V. Proposed Hybrid AI Framework

This study presents a hybrid AI architecture that employs deep learning for perception, machine learning for pattern enhancement, and symbolic reasoning for the application of

logical constraints and domain knowledge. This integration enhances robustness, facilitates comprehension, and increases reliability.
Figure 1 illustrates the proposed hybrid AI architecture. Deep learning models initially analyze raw input data to identify high-level features. Machine learning components enhance these patterns and adapt to accommodate new data. Finally, a layer of symbolic reasoning employs domain-specific rules and constraints to facilitate conclusions that are explicable and manageable. This stratified design achieves an equilibrium between the capacity for learning and openness.

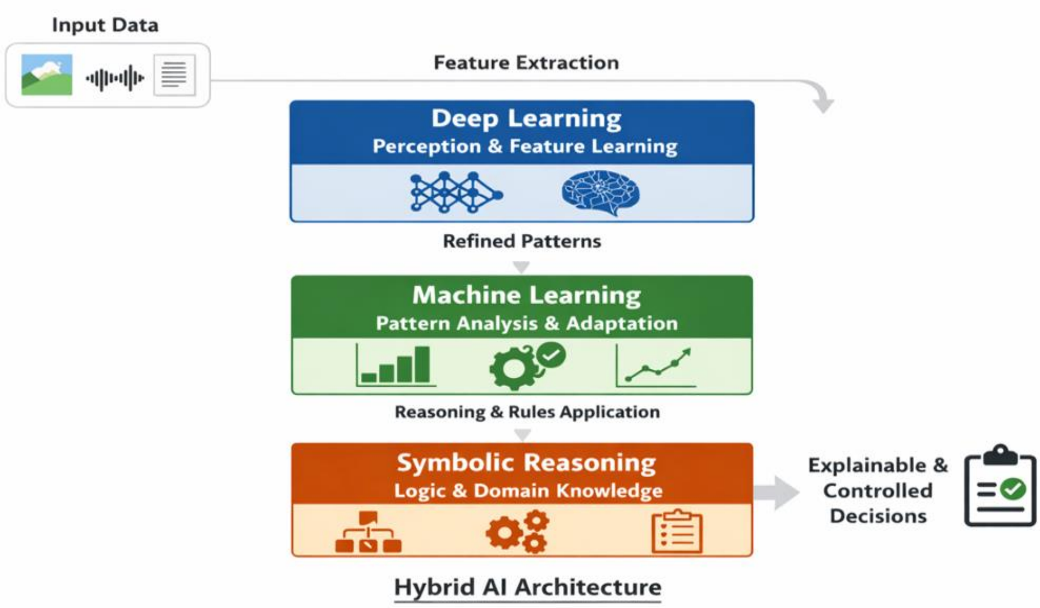

Figure 2. Structure of Hybrid AI.

VI: Results and Discussion

The analytical comparison conducted in this study indicates that no single AI paradigm is universally optimal. Instead, the suitability of an AI approach depends on the nature of the task, the availability of data, the need for interpretability, and the operational context (Dalla et al., 2025; (Karim et al., 2018; Ben Dalla et al., 2024). Deep learning is particularly effective for tasks that require perception and representation learning, such as image analysis, speech processing, and natural language understanding (Apaydın et al., 2022); (Degirmenci and Karal, 2018). Symbolic AI remains advantageous in rule-governed environments where explicit reasoning, constraints, and transparency are required. Machine learning occupies an intermediate position by offering flexibility and moderate interpretability. However, in many practical applications, these paradigms are not mutually exclusive but complementary (Karal and Dalla, 2025); (Çakır et al., 2022); (Sinecen et al., 2009).

As illustrated in **Figure 2**, Hybrid AI emerges as the most balanced solution for real-world intelligent systems. By integrating data-driven learning with structured reasoning, hybrid models can achieve strong predictive performance while preserving explainability and logical consistency. This makes them particularly suitable for domains such as healthcare diagnostics, legal decision support, intelligent tutoring systems, industrial automation, and autonomous systems (Çakır et al., 2022); (Sinecen et al., 2009).

Figure 2 illustrates the evolution of AI paradigms from symbolic thinking to contemporary hybrid systems. The illustration demonstrates how the limitations of early methodologies prompted a shift toward data-driven intelligence and how contemporary research trends increasingly emphasize integration rather than replacement.

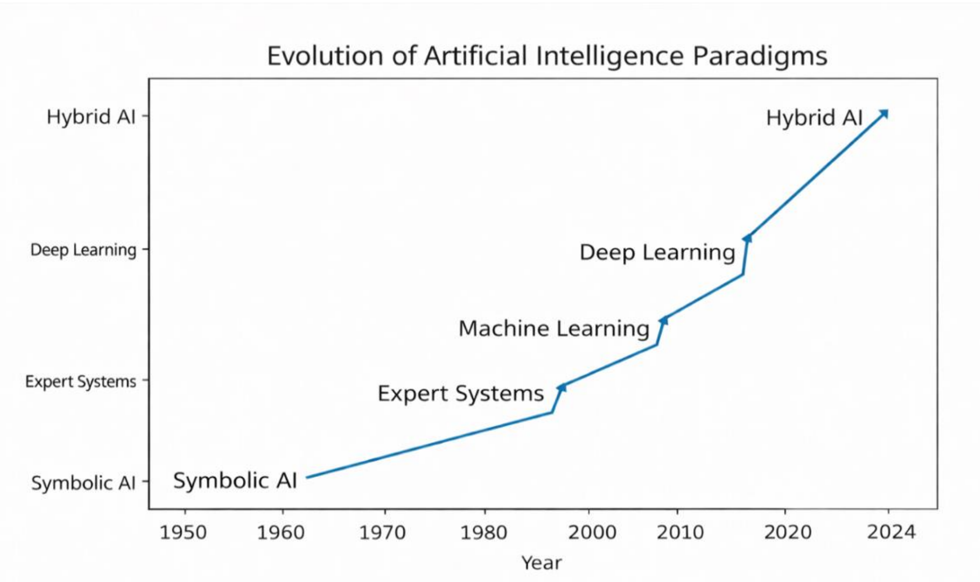

Figure 3. Changes in AI Paradigms

Figure 4 demonstrates a central challenge in AI system design: the trade-off between explain ability and data dependency. Symbolic AI is highly interpretable and requires relatively little data, but it lacks flexibility and learning capacity. Deep learning lies at the opposite extreme, delivering strong performance when abundant data are available but often lacking transparency. Machine learning occupies an intermediate position, while Hybrid AI seeks to balance both dimensions by combining explainable reasoning with data-driven adaptation. This trade-off is crucial when selecting AI methodologies for practical and ethical deployment.

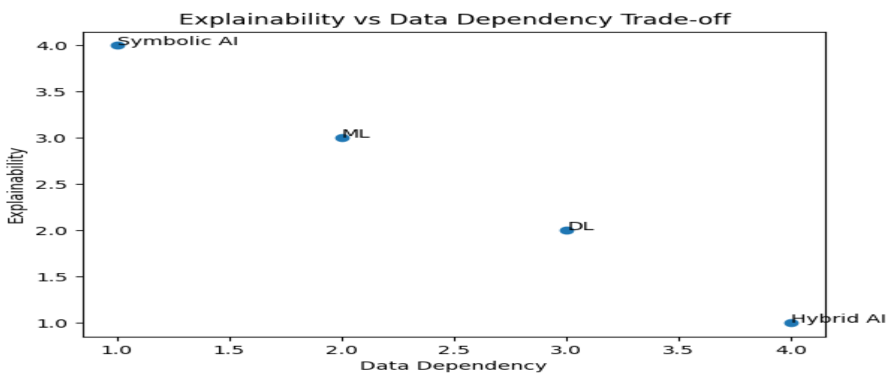

Figure 4. Trade-off between Explainability and Data Dependency

VII: Limitations and Future Work

Although this paper provides a conceptual and comparative analysis of AI paradigms, it has several limitations. First, the proposed Hybrid AI framework has not yet been implemented or experimentally validated. As a result, the conclusions remain theoretical rather than empirical. Second, the comparative discussion is based primarily on conceptual characteristics drawn from the literature and does not include quantitative benchmarking across datasets or tasks. Future work should focus on implementing the proposed framework in a real-world application domain such as healthcare, education, cybersecurity, or intelligent decision support. Experimental evaluation using benchmark datasets would enable comparison with purely symbolic, machine learning, and deep learning approaches in terms of accuracy, explainability, robustness, and computational efficiency. Such validation would significantly strengthen the practical contribution of this work.

VIII. Conclusion

Artificial Intelligence has evolved from symbolic, rule-based systems to highly data-driven learning paradigms. While machine learning and deep learning have dramatically improved AI performance across many domains, they also introduce challenges related to interpretability, transparency, and reliability. Symbolic reasoning, although limited in scalability, continues to offer valuable strengths in logic, structure, and explainable decision-making. This paper has shown that no single paradigm is sufficient for all intelligent applications. Instead, Hybrid AI offers a promising and ethically responsible direction by combining the strengths of symbolic reasoning, machine learning, and deep learning. Such systems are better positioned to meet the demands of modern AI applications, particularly in contexts where performance, explainability, and trust must coexist. Ultimately, the future of artificial intelligence is likely to depend not on choosing between reasoning and learning, but on integrating them in ways that are both technically effective and socially responsible.

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