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Learning from life, enabling artificial intelligence: Scientific historical insights from the Nobel Prize in Physics

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The 2024 Nobel Prize in Physics recognized John Hopfield and Geoffrey Hinton for their transformative contributions to artificial neural networks, sparking widespread debate within the academic community. Why was a physics prize awarded to researchers in artificial intelligence (AI)? How have their achievements influenced the historical trajectory of AI? This article adopts a history-of-science perspective to trace the evolution of neural network technologies, from Hopfield networks to the Boltzmann machine. It examines the interdisciplinary nexus between physics and AI, highlighting its broader implications for future scientific advancements (

Figure **1**).

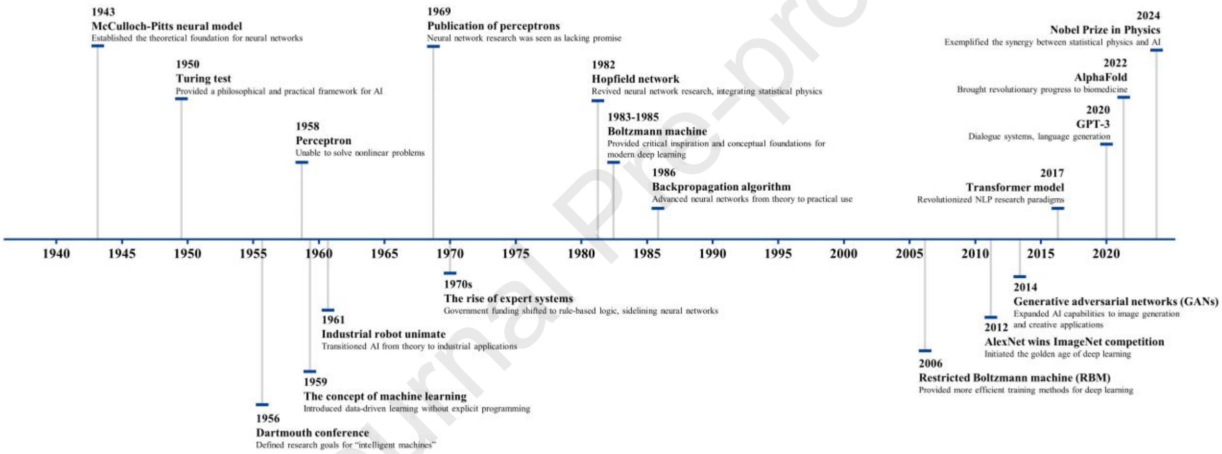

Figure 1. Evolution of artificial intelligence: from perceptrons to deep learning

Abbreviations: AI, artificial intelligence; RBM, restricted Boltzmann machine; GAN, generative adversarial network; NLP, natural language processing; GPT-3, generative pre-trained transformer 3.

The origins of artificial neural networks can be traced to the mid-20th century, marked by significant challenges and breakthroughs. In 1943, Warren McCulloch and Walter Pitts introduced the logical neuron model, establishing the mathematical underpinnings of neural networks. By 1950, Alan Turing had proposed the Turing test, offering a philosophical and practical framework for assessing machine intelligence. The 1956 Dartmouth Conference marked the formal establishment of AI as a discipline, setting explicit goals for the study of intelligent machines. In 1958, Frank Rosenblatt introduced the perceptron, one of the earliest implementations of neural networks. The following year, Arthur Samuel coined the term "machine learning" to describe how machines could enhance their performance through data and experience.

This concept revolutionized AI research by shifting the focus from explicit programming to data-driven learning methodologies. In 1969, Marvin Minsky and Seymour Papert published *Perceptrons: An Introduction to Computational Geometry*, highlighting the limitations of single-layer perceptrons, such as their inability to solve nonlinear problems like Exclusive OR (XOR) [1]. This discovery exposed the theoretical constraints of neural networks and diminished confidence in their potential applications. Concurrently, the United States government reduced funding for AI research, reallocating resources to expert systems. Expert systems demonstrated short-term successes in fields like medical diagnostics and manufacturing optimization, as their clear logical rules and explainability aligned well with industrial demands. However, this shift in policy limited the funding available for early neural network research, further eroding academic enthusiasm. These factors collectively led to a downturn in AI research, known as the "AI Winter" [2]. Against this backdrop, John Hopfield brought a unique physicist's perspective to the field.

In 1982, John Hopfield introduced the Hopfield network, a model designed to emulate associative memory by simulating the brain’s ability to process incomplete or noisy information[3]. Through dynamic state adjustments, the network achieved stable memory storage, marking a pivotal advance in neural network research. This breakthrough not only opened new directions for AI research but also demonstrated practical applications in areas like image restoration and data correction. Leveraging concepts from spin glass theory, Hopfield used energy functions to describe the optimization of neuron states, providing a rigorous mathematical framework for neural networks. This model resolved key challenges in associative memory and introduced a mechanism for finding stable states through energy minimization. Regarded as a pivotal milestone in AI’s resurgence, the Hopfield network reignited academic interest in neural networks and influenced neuroscience by offering critical insights into brain memory and neural dynamics [4].

Building on the foundational work of Hopfield networks, Geoffrey Hinton advanced the field by developing the Boltzmann machine between 1983 and 1985 [5]. This model leveraged probabilistic distributions from statistical physics, enabling neural networks to uncover patterns in data through unsupervised learning. A critical innovation of the Boltzmann machine was its application of thermodynamic principles and simulated annealing algorithms for optimizing network states. By dynamically adjusting temperature parameters, the network could overcome local minima to achieve global optimization, significantly enhancing the efficiency and accuracy of unsupervised learning while broadening its applicability. While modern deep learning theoretical foundations primarily draw from optimization, generalization, and approximation theories, the Boltzmann machine, by integrating concepts from statistical physics, introduced probabilistic methods such as energy-based modeling, significantly inspiring subsequent advancements including restricted Boltzmann machines (RBMs) and deep belief networks (DBNs). Hinton subsequently introduced the RBM, a streamlined variant that significantly simplified the training process and laid the groundwork for modern deep learning [6].

The importance of Boltzmann machines and RBMs extends far beyond theoretical innovation to include profound practical applications [7]. Notably, the multi-layer stacking of RBMs served as the basis for DBNs, which achieved groundbreaking advancements in image classification and speech recognition. The victory of AlexNet in the 2012 ImageNet competition marked a watershed moment in AI, demonstrating the transformative potential of convolutional neural networks (CNNs) in image recognition. This milestone heralded the golden age of deep learning. From revolutionary achievements in image recognition to transformative advances in natural language processing, such as transformer architectures, and from AlphaGo's mastery of board games to the advent of large language models like Chat Generative Pre-trained Transformer (ChatGPT), deep learning has propelled AI into unprecedented frontiers. Additionally, the advent of generative adversarial networks (GANs) in 2014 significantly enhanced the capabilities and broadened the influence of deep learning in fields such as image generation and artistic creation. While previous techniques like autoencoders and variational autoencoders had already been employed in these domains, GANs provided unprecedented realism and flexibility, greatly expanding the creative and practical potential of deep learning. For instance, GAN-based techniques have enabled remarkable breakthroughs in the artistic and creative domains, such as generating highly realistic digital artworks, virtual human images, and synthetic datasets for autonomous driving, significantly reducing the cost and complexity associated with data acquisition. Additionally, deep learning methods, especially CNNs inspired by AlexNet, have profoundly transformed medical diagnostics, achieving groundbreaking accuracy in radiological imaging, ophthalmology, and pathology. These milestones in AI, directly or indirectly, trace their origins to the foundational ideas of Hopfield networks and Boltzmann machines[8]. Collectively, these contributions have laid the groundwork for the flourishing of modern AI, bringing the concept of artificial general intelligence (AGI) closer to reality[9].

The recognition of Hopfield and Hinton through the Nobel Prize not only affirms their technological achievements but also highlights the profound connections between physics and AI. The core role of statistical physics in energy function modeling established a theoretical basis for neural network design. Hopfield and Hinton's work exemplifies how interdisciplinary research can drive breakthroughs in emerging fields, illustrating how statistical physics has influenced neural network design and provided new tools for fundamental science. Conversely, the rise of AI has also propelled innovations in physics. For example, deep learning techniques have become indispensable in material simulation, quantum computing, and high-energy physics, accelerating the modeling and analysis of complex systems. These advancements, including the prediction of new material properties and optimization of quantum circuit designs, underscore AI's transformative role as a new paradigm for scientific research.

Viewed through the lens of the history of science, the 2024 Nobel Prize in Physics stands as a testament to the transformative power of interdisciplinary research. This recognition underscores that groundbreaking scientific achievements often arise at the confluence of diverse disciplines. By advancing artificial neural networks and harmoniously integrating concepts from physics and computational science, the work of Hopfield and Hinton has inaugurated a paradigm of cross-disciplinary collaboration, offering a model for tackling the complex scientific challenges of the future. This paradigm encourages future research to embrace interdisciplinarity to address complex systems and scientific challenges.

As a milestone in the era of intelligence, the 2024 Nobel Prize in Physics not only highlights AI's past achievements but also underscores future challenges beyond technical innovation. Ethical issues such as algorithmic biases, privacy protection, and responsible governance, alongside sustainability concerns around energy consumption, require urgent attention. Addressing these challenges calls for enhanced interdisciplinary cooperation among computer scientists, ethicists, policymakers, and social scientists. Such collaborative efforts will guide AI's responsible and sustainable integration into society, illuminating clear paths for future research and scientific discovery.

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DECLARATION OF COMPETING INTERESTS

All authors declare that they have no conflicts of interest. .

AUTHOR CONTRIBUTIONS

Zongzhen Wu: conceptualization, writing – original draft. **Lu Zhang:** investigation, resources. **Qiangyu Xiang:** formal analysis, visualization. **Xiaobo Zhao:** writing – review & editing. **Huan Liu:** conceptualization, supervision, funding acquisition, writing – review & editing.

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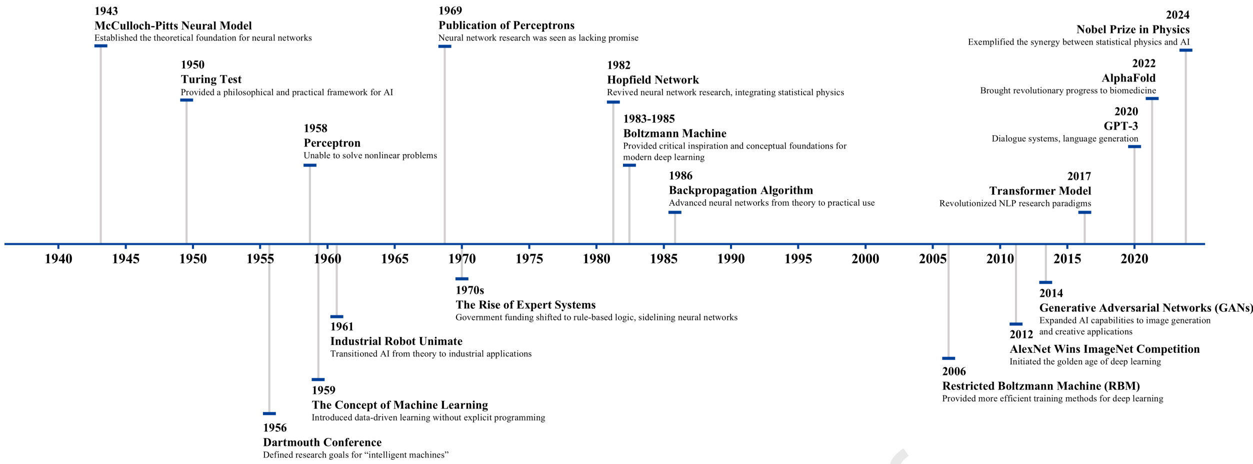
1943
McCulloch-Pitts Neural Model
Established the theoretical foundation for neural networks
1950
Turing Test
Provided a philosophical and practical framework for AI
1958
Perceptron
Unable to solve nonlinear problems
1969
Publication of Perceptrons
Neural network research was seen as lacking promise
1982
Hopfield Network
Revived neural network research, integrating statistical physics
1983-1985
Boltzmann Machine
Provided critical inspiration and conceptual foundations for modern deep learning
1986
Backpropagation Algorithm
Advanced neural networks from theory to practical use
2024
Nobel Prize in Physics
Exemplified the synergy between statistical physics and AI
2022
AlphaFold
Brought revolutionary progress to biomedicine
2020
GPT-3
Dialogue systems, language generation
2017
Transformer Model
Revolutionized NLP research paradigms
1940
1945
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
1970s
The Rise of Expert Systems
Government funding shifted to rule-based logic, sidelining neural networks
1961
Industrial Robot Unimate
Transitioned AI from theory to industrial applications
1959
The Concept of Machine Learning
Introduced data-driven learning without explicit programming
1956
Dartmouth Conference
Defined research goals for "intelligent machines"
2014
Generative Adversarial Networks (GANs)
Expanded AI capabilities to image generation and creative applications
2012
AlexNet Wins ImageNet Competition
Initiated the golden age of deep learning
2006
Restricted Boltzmann Machine (RBM)
Provided more efficient training methods for deep learning

Declaration of Interest Statement

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