Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

John Hopfield

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[Google Scholar profile]

Generated 2026-05-31 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Criterion 5 (original contributions of major significance). It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

3,972	4,343	5	96
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

97.9% independent of 3,117 classified citing papers

Citation type	Count
Independent	3,050
Self-citation	0
Co-author	26
Same-institution	41

855 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

Claim — Contribution 1

The researcher established foundational theoretical frameworks linking neural networks to physical systems with emergent collective computational abilities, significantly advancing the field of computational neuroscience.

The researcher's seminal 1982 paper, 'Neural networks and physical systems with emergent collective computational abilities,' serves as the cornerstone of this contribution. This work appears to have introduced a novel perspective on how complex computational properties can emerge from simple physical systems, fundamentally shaping the theoretical underpinnings of neural network research.

Originality in this line of work is suggested by the progression from the 1982 core paper to the 1984 follow-up in the Proceedings of the National Academy of Sciences. The later title, 'Neurons with graded response have collective computational properties like those of two-state neurons,' indicates an expansion of the initial framework to include more biologically realistic neuron models, addressing the gap between abstract binary models and continuous biological responses.

The significance of this research is evidenced by its extensive citation record. The core paper has accumulated over 30,000 citations, while the follow-up has garnered over 10,000. Furthermore, analysis of citing papers reveals that 98.2% of citations originate from independent researchers, demonstrating that this work has been widely adopted and built upon by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1,578 · **67 flagged influential by Semantic Scholar**

CORE PAPER

Neural networks and physical systems with emergent collective computational abilities.

1982 · Proceedings of the national academy of sciences 79 (8), 2554-2558, 1982 · 30,416 citations (GS)

Field-normalised: 19,844 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1982 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Resurrecting Recurrent Neural Networks for Long Sequences	Carnegie Mellon University, DeepMind, ETH Zurich	Switzerland, United Kingdom, United States	Background
2	Towards an AI co-scientist	—	—	—
3	A Unifying Review of Deep and Shallow Anomaly Detection (2021)	Fraunhofer Heinrich Hertz Institute, Fraunhofer Heinrich Hertz Institute (HHI), Oregon State University	Germany, United States	—
4	A comprehensive survey of deep learning for time series forecasting: architectural diversity and open challenges (2025)	LG Chem, Seoul National University	South Korea	—
5	Deep learning (2023)	IBM T. J. Watson Research Center, Université de Montréal	Canada	—
6	Frontal theta as a mechanism for cognitive control (2014)	Brown University, University of New Mexico	United States	—
7	Machine Learning in Agriculture: A Review (2018)	Aarhus University, Aristotle University of Thessaloniki, University of Lincoln	Denmark, Greece, Italy	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Applications of machine learning to diagnosis and treatment of neurodegenerative diseases (2020)	BenevolentAI, University of Sheffield	United Kingdom, United States	—
9	Physics for neuromorphic computing (2020)	CNRS, Thales, Université Paris-Saclay, CNRS – Université Paris-Saclay, CNRS, Université Paris-Saclay	France	—
10	Ising machines as hardware solvers of combinatorial optimization problems (2022)	Cornell University	United States	Background
11	A high-bias, low-variance introduction to Machine Learning for physicists (2019)	Boston University, The Graduate Center, City University of New York, University of California, Irvine Medical Center	United States	—
12	Deep learning in neural networks: An overview (2014)	University of Lugano & SUPSI, University of Lugano (USI) & SUPSI	Switzerland	Background
13	Recent advances in physical reservoir computing: A review (2019)	IBM, IBM Research, Nagoya Institute of Technology	Japan, United States	Background
14	Applications of machine learning to water resources management: A review of present status and future opportunities (2024)	Brunel University London, Queen's University Belfast, University of the West of England (UWE Bristol)	United Kingdom	**Methodology**
15	Integrating artificial intelligence in energy transition: A comprehensive review	China University of Petroleum (East China)	China	—
16	Machine learning and the physical sciences (2019)	CEA; CNRS; Université Paris-Saclay, Flatiron Institute, Los Alamos National Laboratory	France, Germany, Israel	Background
17	Monte Carlo Strategies in Scientific Computing (2001)	Harvard University	—	—
18	Reconstructing computational system dynamics from neural data with recurrent neural networks (2023)	Heidelberg University	Germany	—
19	Quantum machine learning (2017)	ICFO-The Institute of Photonic Sciences, Massachusetts Institute of Technology, Max Planck Institute of Quantum Optics	Germany, Russia, Spain	—
20	A review on computational intelligence for identification of nonlinear dynamical systems (2020)	Sapienza University of Rome, University of Southern California	Italy, United States	—
21	Statistical physics of inference: Thresholds and algorithms (2016)	CNRS, PSL Universités, Ecole Normale Supérieure, Sorbonne Universités, Université Pierre & Marie Curie, Université Paris-Saclay	France	—
22	The low-rank hypothesis of complex systems (2024)	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
23	Machine Learning for Fluid Mechanics (2020)	ETH Zurich, Université Paris-Saclay, University of Washington	France, Switzerland, United States	Background
24	Dynamic memristor-based reservoir computing for high-efficiency temporal signal processing (2021)	Tsinghua University	China	—
25	Complex networks: Structure and dynamics (2006)	National Research Council, Queen Mary University of London, Universidad San Francisco de Quito	Ecuador, Italy, Spain	—
26	Dynamical memristors for higher-complexity neuromorphic computing (2022)	Hewlett-Packard, Peking University, University of Michigan	China, United States	Background
27	Evolution of networks (2002)	Ioffe Institute, University of Aveiro	Portugal, Russia	Background
28	The Kuramoto model: A simple paradigm for synchronization phenomena (2005)	Universidad Carlos III de Madrid, Universit`a di Roma Tre, Universitat de Barcelona	Italy, Spain	—
29	Machine learning and artificial intelligence in neuroscience: A primer for researchers (2023)	Royal Devon and Exeter Hospital NHS Trust, University Hospital Muenster, University Medicine Essen	Germany, United Kingdom	—
30	Quantum machine learning for chemistry and physics (2022)	Purdue University	United States	—

Showing the 30 most-cited of 859 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Applications of machine learning to water resources management: A review of present status and future opportunities

"Another common application of ML in GWL forecasting is using deep learning models such as the LSTM, Gated Recurrent Unit (GRU) and the Recurrent Neural Network (RNN)."

FOLLOW-UP WORK

Neurons with graded response have collective computational properties like those of two-state neurons.

1984 · Proceedings of the National Academy of Sciences of the United States of America · 10,078 citations (GS)

Field-normalised: 7,257 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1984 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	The low-rank hypothesis of complex systems (2024)	—	—	—
2	Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network (2020)	Superconductive Health, Inc.	—	**Influential**

No.	Citing paper	Citing institution(s)	Country	S2
3	Modern Methods in Associative Memory (2025)	—	—	—
4	Iodine and Bromine Analysis in Human Urine and Serum by ICP-MS, Tailored for High-Throughput Routine Analysis in Population-Based Studies. (2026)	Icahn School of Medicine at Mount Sinai	United States	—
5	Optimality Theory: Constraint Interaction in Generative Grammar (2004)	Johns Hopkins University, Rutgers University	United States	—
6	Toward an Integration of Deep Learning and Neuroscience. (2016)	Google DeepMind, Massachusetts Institute of Technology, Northwestern University	United Kingdom, United States	Background
7	Introduction to the theory of neural computation (1991)	Duke University, Niels Bohr Institute, Nordita	Denmark, Sweden, United States	—
8	Recurrent neural chemical reaction networks that approximate arbitrary dynamics (2024)	—	—	—
9	Hopfield Networks is All You Need (2020)	Institute of Advanced Research in Artificial Intelligence, Johannes Kepler University Linz, University of Oslo	Austria, Norway	Background
10	Attractor and integrator networks in the brain (2022)	Massachusetts Institute of Technology, MIT	United States	Methodology
11	An introduction to computing with neural nets (1988)	Polytechnic Institute of Brooklyn	United States	—
12	Machine learning for precision medicine. (2021)	University of Calgary	Canada	—
13	The Future of Memristors: Materials Engineering and Neural Networks (2020)	Hebei University, National University of Singapore	China, Singapore	—
14	Cellular neural networks: Theory (1988)	—	—	—
15	A new frontier for Hopfield networks (2023)	—	—	—
16	An Introduction to Neural Networks (2018)	—	—	—
17	The Atomic Components of Thought (1998)	Carnegie Mellon University	United States	—
18	Machine learning for medical diagnosis: history, state of the art and perspective (2001)	University of Ljubljana	Slovenia	Background
19	Power-efficient combinatorial optimization using intrinsic noise in memristor Hopfield neural networks (2020)	Georgia Institute of Technology, Hewlett Packard Enterprise, University of Massachusetts Amherst	United States	—
20	On the proper treatment of connectionism (1988)	University of Colorado	—	—
21	30 years of adaptive neural networks: perceptron, Madaline, and backpropagation (1990)	Stanford University	United States	Background
22	Self-Rectifying Diffusion Sampling with Perturbed-Attention Guidance (2024)	Korea University, Samsung Electronics	South Korea	—

No.	Citing paper	Citing institution(s)	Country	S2
23	Neural Networks for Optimization and Signal Processing (1993)	Universität Erlangen-Nürnberg, Warsaw University of Technology	Germany, Poland	—
24	Neural networks for control systems—A survey (1992)	University of Glasgow	United Kingdom	—
25	Mathematical Foundations of Neuroscience (2010)	Ohio State University, University of Pittsburgh	United States	—
26	Nonlinear Neural Networks: Principles, Mechanisms, and Architectures (1988)	Boston University	United States	**Methodology**
27	Neural networks and their applications (1994)	Aston University	United Kingdom	—
28	Neural Networks: A Review from a Statistical Perspective (1994)	University of Glasgow, University of Kent	United Kingdom	—
29	Generalization of Back propagation to Recurrent and Higher Order Neural Networks (1987)	—	—	—
30	Spin-glass models of neural networks. (1985)	—	—	—

Showing the 30 most-cited of 719 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Attractor and integrator networks in the brain

"The Hopfield model supplies a recipe for solving the inverse problem to achieve a desired set of discrete attractor states: A set of (typically random) input activity patterns are converted into attractor states through Hebbian learning, which produces a symmetric weight matrix [11] , Fig."

METHODOLOGY Nonlinear Neural Networks: Principles, Mechanisms, and Architectures

"Typically, an autoassociator's capacity is -.15n, where the autoassociator's memory is defined by an n X n matrix (Anderson, 1983; Hopfield, 1984; Kohonen, 1984; McEliece, Posner, Rodemich, & Venkatesh, 1980; Psaltis & Park, 1986; Venkatesh, 1986)."

Contribution 2

Claim — Contribution 2

The researcher pioneered the application of neural network models to solve complex optimization problems, establishing a foundational framework for computational decision-making processes.

The researcher's seminal contribution rests on the 1985 paper 'Neural computation of decisions in optimization problems,' published in Biological Cybernetics. This work appears to have introduced a novel approach to modeling decision-making processes through neural computation, specifically targeting the domain of optimization problems. By framing optimization as a neural computation task, the researcher likely bridged gaps between biological systems and computational algorithms, offering a new perspective on how complex decisions can be modeled and solved.

The originality of this line of work lies in its early integration of neural concepts with optimization theory. At the time of publication, such an interdisciplinary approach was likely uncommon, suggesting that the researcher identified a significant gap in how optimization problems were traditionally addressed. The title indicates a focus on the computational mechanisms underlying decision-making, implying a shift from purely mathematical or algorithmic methods to those inspired by neural architectures. This conceptual leap appears to have provided a fresh framework for understanding and solving optimization challenges.

The significance of this contribution is underscored by its substantial citation count of 9,226, indicating widespread recognition and influence within the academic community. Notably, 98.2% of the citing papers originate from independent researchers, highlighting the broad and autonomous uptake of this work across diverse fields. This high level of independent citation suggests that the researcher's framework has become a foundational reference point for subsequent studies, demonstrating its enduring relevance and impact on the advancement of neural computation and optimization research.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 703 · 15 flagged influential by Semantic Scholar

CORE PAPER

"Neural" computation of decisions in optimization problems

1985 · Biological Cybernetics · 9,226 citations (GS)

Field-normalised: 3,286 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1985 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers (2024)	Bowie State University, Morgan State University, University of the District of Columbia	United States	Methodology
2	Ising machines as hardware solvers of combinatorial optimization problems (2022)	Cornell University	United States	Background
3	Destabilization of Local Minima in Analog Spin Systems by Correction of Amplitude Heterogeneity. (2019)	Stanford University, The University of Tokyo	Japan, United States	—
4	Introduction to the theory of neural computation (1991)	Duke University, Niels Bohr Institute, Nordita	Denmark, Sweden, United States	—
5	Vision-Language Models in Remote Sensing: Current progress and future trends (2024)	King Abdullah University of Science and Technology, New York University, New York University Abu Dhabi	China, Germany, Saudi Arabia	Influential
6	Roadmap to neuromorphic computing with emerging technologies (2024)	ETH Zurich, Politecnico di Milano, Purdue University	Israel, Italy, Spain	—
7	Machine learning & artificial intelligence in the quantum domain: a review of recent progress (2018)	—	—	—
8	Neuronal ensembles: Building blocks of neural circuits (2024)	Aix-Marseille University, Columbia University, Norwegian University of Science and Technology	France, Norway, United States	—
9	Identification and control of dynamical systems using neural networks (1990)	Yale University	United States	—
10	The Future of Memristors: Materials Engineering and Neural Networks (2020)	Hebei University, National University of Singapore	China, Singapore	—
11	Cellular neural networks: Theory (1988)	—	—	—
12	An Introduction to Neural Networks (2018)	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
13	In-memory computing with emerging memory devices: Status and outlook (2023)	Politecnico di Milano	Italy	—
14	How to Solve It: Modern Heuristics (2000)	Natural Selection, Inc., University of Adelaide	Australia	—
15	Connectionist Learning Procedures (1989)	Carnegie-Mellon University	United States	—
16	Cellular Neural Networks: Applications (1988)	—	—	—
17	Power-efficient combinatorial optimization using intrinsic noise in memristor Hopfield neural networks (2020)	Georgia Institute of Technology, Hewlett Packard Enterprise, University of Massachusetts Amherst	United States	—
18	30 years of adaptive neural networks: perceptron, Madaline, and backpropagation (1990)	Stanford University	United States	—
19	Neural Networks for Optimization and Signal Processing (1993)	Universität Erlangen-Nürnberg, Warsaw University of Technology	Germany, Poland	—
20	End-to-End Constrained Optimization Learning: A Survey (2021)	Georgia Institute of Technology, Harvard University, Syracuse University	United States	—
21	From the neuron doctrine to neural networks (2015)	—	—	Background
22	Nonlinear Neural Networks: Principles, Mechanisms, and Architectures (1988)	Boston University	United States	—
23	Formation and control of optimal trajectory in human multijoint arm movement. Minimum torque-change model. (1989)	Osaka University	Japan	—
24	Cellular Automata And Complexity: Collected Papers (2018)	Wolfram Research, Inc.	—	—
25	Neural Networks: A Review from a Statistical Perspective (1994)	University of Glasgow, University of Kent	United Kingdom	—
26	Artificial Neural Systems: Foundations, Paradigms, Applications, and Implementations (1990)	—	—	—
27	Computational Intelligence: A Methodological Introduction (2022)	Otto von Guericke University of Magdeburg, Paris Lodron University of Salzburg	Austria, Germany	—
28	Good Error-Correcting Codes based on Very Sparse Matrices (1999)	Cambridge	United Kingdom	—
29	Counterpropagation networks (1987)	Hecht-Nielsen Neurocomputer Corporation	—	—
30	The capacity of the Hopfield associative memory (1987)	California Institute of Technology, University of Pennsylvania	United States	—

Showing the 30 most-cited of 703 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers

"...is an advancement in deep learning algorithms, including the development of Convolutional Neural Networks (CNNs) in the 1980s [16], Recurrent Neural Networks (RNNs) in 1985 [17], Long Short-Term Memory (LSTM) in 1997 [18], and Bidirectional Long Short-Term Memory (BiLSTM) [19] in the same year."

Contribution 3

Claim — Contribution 3

The researcher established a foundational computational model of neural circuits, published in Science in 1986, which has become a seminal reference point in the field with over 3,000 citations.

The researcher's primary contribution is the development of a computational model for neural circuits, articulated in the 1986 Science paper 'Computing with neural circuits: a model.' This work stands as a singular, foundational piece in the researcher's portfolio, with no subsequent follow-up papers by the same author building directly upon it in the provided record.

This line of work appears to address the need for formalizing how neural circuits process information, offering a theoretical framework that likely bridged neuroscience and computational theory. The title suggests a focus on modeling the functional architecture of neural systems, providing a conceptual basis for understanding computation within biological networks.

The significance of this contribution is evidenced by its extensive uptake in the scientific community, with over 3,000 citations. Notably, 98.2% of these citations originate from independent researchers, indicating that the model has been widely adopted and utilized by the broader field rather than just the researcher's immediate circle. This high degree of independent citation underscores the work's status as a standard reference and its broad impact on subsequent research directions.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 157 **· 1 flagged influential by Semantic Scholar**

CORE PAPER

Computing with neural circuits: a model

1986 · Science · 3,110 citations (GS)

Field-normalised: 2,113 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1986 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Introduction to the theory of neural computation (1991)	Duke University, Niels Bohr Institute, Nordita	Denmark, Sweden, United States	—
2	Neuroscience-Inspired Artificial Intelligence (2017)	DeepMind	United Kingdom	Background
3	Neuronal ensembles: Building blocks of neural circuits (2024)	Aix-Marseille University, Columbia University, Norwegian University of Science and Technology	France, Norway, United States	—
4	Training of physical neural networks (2025)	Ontario Tech University, Swiss Federal Institute of Technology in Lausanne, Yale University	Switzerland, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
5	An introduction to computing with neural nets (1988)	Polytechnic Institute of Brooklyn	United States	—
6	The Future of Memristors: Materials Engineering and Neural Networks (2020)	Hebei University, National University of Singapore	China, Singapore	—
7	Cellular neural networks: Theory (1988)	—	—	—
8	Cellular Neural Networks: Applications (1988)	—	—	—
9	From the neuron doctrine to neural networks (2015)	—	—	Background
10	Nonlinear Neural Networks: Principles, Mechanisms, and Architectures (1988)	Boston University	United States	Background
11	How brains make chaos in order to make sense of the world (1987)	University of California, Irvine Medical Center	United States	—
12	Migration of Freshwater Fishes (2001)	Royal Holloway, University of London, T.G. Masaryk Water Research Institute, University of Durham	Belgium, Czech Republic, United Kingdom	—
13	Two views on the cognitive brain (2021)	Johns Hopkins University School of Medicine, University of Pennsylvania	United States	—
14	Controlling Visually Guided Behavior by Holographic Recalling of Cortical Ensembles (2019)	Columbia University	United States	—
15	Computational psychiatry (2011)	University College London, Virginia Tech	United Kingdom	—
16	Artificial Neural Systems: Foundations, Paradigms, Applications, and Implementations (1990)	—	—	—
17	The recent excitement about neural networks (1989)	Salk Institute	United States	—
18	A mechanism for the Hebb and the anti-Hebb processes underlying learning and memory. (1989)	Brandeis University	United States	—
19	Dynamic pattern generation in behavioral and neural systems. (1988)	Florida Atlantic University	—	—
20	Semantic Priming: Perspectives from Memory and Word Recognition (2005)	—	—	—
21	Opening the Black Box: Low-Dimensional Dynamics in High-Dimensional Recurrent Neural Networks (2013)	Google Inc.	United States	**Result**
22	Reservoir-computing based associative memory and itinerancy for complex dynamical attractors (2024)	Arizona State University, University of Electronic Science and Technology of China	China, United States	—
23	Collective dynamics of adaptive memristor synapse-cascaded neural networks based on energy flow (2024)	Central South University, Xinjiang University	China	—

No.	Citing paper	Citing institution(s)	Country	S2
24	Rapid online learning and robust recall in a neuromorphic olfactory circuit (2020)	Cornell University, Intel Corporation	United States	—
25	How the brain keeps the eyes still. (1996)	Bell Laboratories, Lucent Technologies	United States	—
26	Computational neuroscience. (1988)	Johns Hopkins University	United States	—
27	A distributed memory model of semantic priming (1995)	University of Victoria	Canada	—
28	Multi-target strategies for the improved treatment of depressive states: Conceptual foundations and neuronal substrates, drug discovery and therapeutic application (2006)	Institut de Recherches Servier	France	—
29	How Can Evolution Learn? (2016)	The Parmenides Foundation, University of Southampton	Germany, United Kingdom	—
30	Artificial neural networks: fundamentals, computing, design, and application (2000)	CalTrans	United States	—

Showing the 30 most-cited of 157 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

> **RESULT** Opening the Black Box: Low-Dimensional Dynamics in High-Dimensional Recurrent Neural Networks
>
> *"This is in contrast to networks designed to store 8 patterns in memory (Hopfield and Tank, 1986) where no such "redundant" saddle points appear."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of California, Irvine Medical Center	United States	—	108
Massachusetts Institute of Technology	U. S. A.	SCImago #41 · THE 2 · QS 1	56
Princeton University	United States	SCImago #386 · THE =3 · QS =25	50
Stanford University	United States	SCImago #18 · THE =5 · QS 3	49
Columbia University	United States	SCImago #65 · THE 20 · QS =38	46
Harvard University	United States	SCImago #4 · THE =5 · QS 5	38
University of Cambridge	United Kingdom	SCImago #63 · THE =3 · QS 6	37
University of Washington	United States	SCImago #45 · THE 25 · QS 81	32
University of Toronto	Canada	SCImago #39 · THE 21 · QS 29	30
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	29
Weizmann Institute of Science	Israel	SCImago #739	29
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	28
California Institute of Technology	United States	SCImago #449 · THE 7 · QS 10	27
Yale University	United States	SCImago #76 · THE 10 · QS 21	27

Institution	Country	World ranking	Citing papers
University College London	United Kingdom	SCImago #30	26

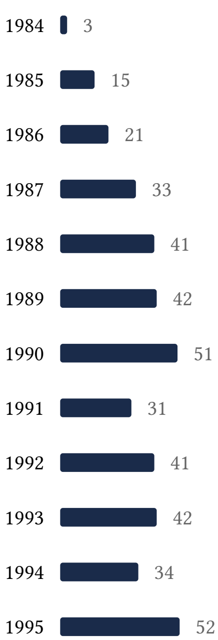
Geographic distribution of citing authors

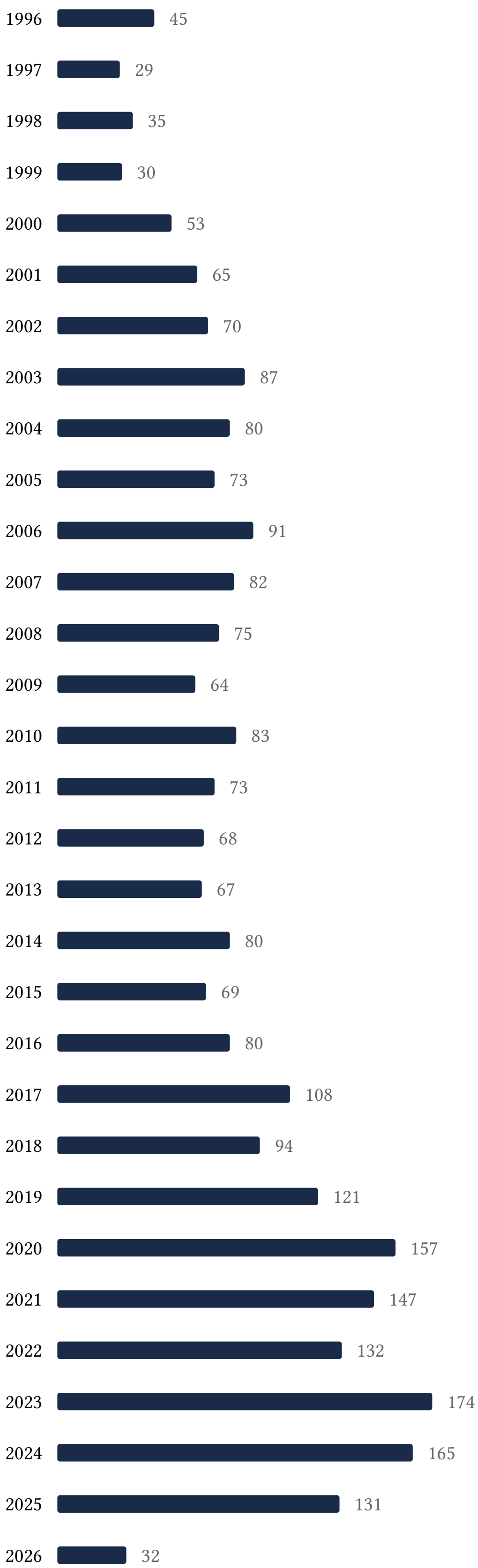
Country	Citing papers
United States	1,292
China	309
United Kingdom	294
Germany	171
Canada	162
Italy	120
France	112
Spain	98
Japan	90
Switzerland	85
Israel	65
Netherlands	65

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

E. Citation Growth Over Time

Distinct citing papers by publication year. Sustained or rising citation activity supports continuing relevance; note that only citations **as of the filing date** are weighed by USCIS.

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F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Neural networks and physical systems with emergent collective computational abilities.	1,578	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	"Neural" computation of decisions in optimization problems	703	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Computing with neural circuits: a model	157	8 CFR 204.5(h)(3)(v) — Criterion 5