Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

Judea Pearl

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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

2,598	2,801	107	127
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.

98.8% independent of 914 classified citing papers

Citation type	Count
Independent	903
Self-citation	7
Co-author	1
Same-institution	3

1,684 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 frameworks for probabilistic and causal reasoning in intelligent systems, creating a seminal theoretical basis widely adopted across independent scientific communities.

The researcher's contribution centers on the development of rigorous frameworks for probabilistic and causal inference, anchored by the seminal 1995 book 'Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.' This core work appears to have defined the structural logic for how intelligent systems process uncertainty and plausible inference.

This line of work addresses the critical challenge of formalizing reasoning under uncertainty. The progression from the 1995 core text to subsequent papers on 'Causal diagrams for empirical research' and 'Equivalence and synthesis of causal models' suggests a sustained effort to refine and expand these theoretical foundations. The titles indicate a shift toward applying these probabilistic networks to empirical causal analysis and model synthesis, bridging theoretical inference with practical empirical research methodologies.

The significance of this contribution is evidenced by the extensive uptake of the core work, which has accumulated over 35,000 citations. Furthermore, the high citation counts for the follow-up papers, combined with the fact that nearly 99% of citing papers originate from independent researchers, demonstrates that this framework has become a standard, widely adopted tool across diverse scientific disciplines rather than a niche or self-referential achievement.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 364 · **9 flagged influential by Semantic Scholar**

CORE PAPER

Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference

1995 · Morgan Kaufmann Publishers (Book) · 35,376 citations (GS)

Field-normalised: 11,580 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1995 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Reasoning or Reciting? Exploring the Capabilities and Limitations of Language Models Through Counterfactual Tasks (2024)	Boston University, MIT	United States	Background
2	Ant colony optimization (2006)	Université Libre de Bruxelles, Université Libre de Bruxelles (ULB)	Belgium	—
3	Deep Learning for Health Informatics (2016)	Imperial College London	United Kingdom	Background
4	AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems (2022)	—	—	Background
5	Basic techniques (2007)	Inria, University of Trento	France, Italy	—
6	Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models (2022)	3M, Google, University of Notre Dame	United States	—
7	Machine Learning Methods for Small Data Challenges in Molecular Science (2023)	Michigan State University, Wuhan Textile University	China, United States	—
8	Deep learning (2016)	National Cancer Center, Université de Montréal	Canada, South Korea	—

No.	Citing paper	Citing institution(s)	Country	S2
9	Machine Learning in Agriculture: A Review (2018)	Aarhus University, Aristotle University of Thessaloniki, University of Lincoln	Denmark, Greece, Italy	—
10	Causal inference for time series (2023)	German Aerospace Center, German Aerospace Center (DLR), Max Planck Institute for Biogeochemistry	Germany, Spain	—
11	Normalizing Flows for Probabilistic Modeling and Inference (2021)	DeepMind, Google DeepMind, Johns Hopkins University	United Kingdom, United States	Background
12	DeepWalk: Online Learning of Social Representations (2014)	Stony Brook University	United States	**Methodology**
13	Bayesian Data Analysis (1995)	Columbia University, Harvard University, Murdoch Children's Research Institute	Australia, United States	—
14	Bayesian inference in physics (2011)	Max-Planck-Institute for Plasmaphysics	—	—
15	Modern Information Retrieval (1999)	Universidad de Chile, Universidad Federal de Minas Gerais	Brazil, Chile	—
16	A Survey on Causal Inference (2021)	Alibaba Group, Purdue University, University of Georgia	United States	—
17	Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable (2014)	Harvard University, University of Wisconsin	United States	—
18	The Blessings of Multiple Causes (2020)	Columbia University	United States	—
19	Identification of core-periphery structure in networks (2015)	University of Michigan	United States	—
20	Modern views of machine learning for precision psychiatry (2022)	Headspace Health, Lehigh University, New York University Grossman School of Medicine	United States	Background
21	Natural Language Processing (almost) from Scratch (2011)	Google, Idiap Research Institute, Microsoft	Switzerland, United States	—
22	Deep Learning (2016)	Google, Université de Montréal	Canada, United States	—
23	Variational Inference: A Review for Statisticians (2017)	Columbia University, University of California, Irvine Medical Center	United States	—
24	Stochastic Variational Inference (2013)	University of California, Irvine Medical Center	United States	**Methodology**
25	A Fast Learning Algorithm for Deep Belief Nets (2006)	National University of Singapore, University of Toronto	Canada, Singapore	—
26	Graphical Models, Exponential Families, and Variational Inference (2008)	University of California, Irvine Medical Center	United States	—
27	An Introduction to Variational Methods for Graphical Models (1999)	Massachusetts Institute of Technology, University College London, University of	United Kingdom, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
		California, Irvine Medical Center		
28	Principles of data mining. (2007)	Imperial College London	United Kingdom	—
29	Iron behaving badly: inappropriate iron chelation as a major contributor to the aetiology of vascular and other progressive inflammatory and degenerative diseases.	The University of Manchester	United Kingdom	Background
30	A comprehensive survey on machine learning for networking: evolution, applications and research opportunities (2018)	Universidad del Cauca, University of Waterloo	Canada, Colombia	—

Showing the 30 most-cited of 364 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 DeepWalk: Online Learning of Social Representations

"Techniques to address this problem typically use approximate inference techniques [31, 35] to leverage the dependency information to improve classification results."

METHODOLOGY Stochastic Variational Inference

"Statistical machine learning research has addressed some of these challenges by developing the field of probabilistic modeling, a field that provides an elegant approach to developing new methods for analyzing data (Pearl, 1988; Jordan, 1999; Bishop, 2006; Koller and Friedman, 2009; Murphy, 2012)."

FOLLOW-UP WORK

Causal diagrams for empirical research (with Discussions)

2022 · Probabilistic and causal inference: The works of Judea Pearl, 255-316, 2022 · 4,022 citations (GS)

Field-normalised: 20 Semantic Scholar citations place it in the top 10% of Mathematics papers from 2022 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

FOLLOW-UP WORK

Equivalence and synthesis of causal models

2022 · Probabilistic and causal inference: The works of Judea Pearl, 221-236, 2022 · 2,067 citations (GS)

Field-normalised: 1,501 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2022 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

Contribution 2

Claim — Contribution 2

The researcher advanced the scientific understanding of cause and effect through a seminal 2009 paper and subsequent works on causal inference and mediation analysis.

The researcher's contribution centers on the foundational work titled 'Causality' (2009), which serves as the core of a sustained line of inquiry into causal inference. This body of work is further developed in the 2018 book 'The book of why: The new science of cause and effect' and the 2022 paper 'Direct and indirect effects,' indicating a comprehensive approach to defining and measuring causal relationships.

This line of work appears to address the methodological challenges of distinguishing correlation from causation. The progression from the 2009 core paper to later publications suggests an effort to formalize causal reasoning and expand its application to complex scenarios involving direct and indirect effects, thereby providing a structured framework for analyzing cause and effect.

The significance of this contribution is evidenced by the high citation counts of the core paper and its follow-ups. Furthermore, the fact that 98.9% of citing papers originate from independent researchers indicates that this work has been widely adopted and utilized by the broader scientific community, confirming its substantial impact on the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 625 · **16 flagged influential by Semantic Scholar**

CORE PAPER

Causality

2009 · Cambridge university press, 2009 · 33,166 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	What do we need to build explainable AI systems for the medical domain? (2017)	Medical University Graz, The University of Manchester, Universität Hamburg	Austria, Cyprus, Germany	—
2	On the Opportunities and Risks of Foundation Models (2021)	Stanford Institute for Human-Centered Artificial Intelligence, Stanford University	United States	—
3	Mechanistic Interpretability for AI Safety – A Review (2024)	University of Amsterdam	Netherlands	—
4	Foundations & Trends in Multimodal Machine Learning: Principles, Challenges, and Open Questions (2022)	Carnegie Mellon University	United States	—
5	Toward Causal Representation Learning (2021)	Google, Google Research, Max Planck Institute for Intelligent Systems	Canada, Germany, Netherlands	—
6	Meta-analysis and Mendelian randomization: A review. (2019)	—	—	—
7	Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models (2022)	3M, Google, University of Notre Dame	United States	—
8	Kernel Instrumental Variable Regression	Massachusetts Institute of Technology, University College London	United Kingdom, United States	—
9	Recent Developments in the Econometrics of Program Evaluation	Michigan State University	United States	—
10	Artificial Intelligence for Science in Quantum, Atomistic, and Continuum Systems (2025)	California Institute of Technology, Cornell University, Harvard Medical School	Canada, Germany, Netherlands	—
11	Machine learning for microbiologists (2023)	City University of New York, City University of New York (CUNY), CUNY Graduate School of Public Health and Health Policy	Italy, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
12	Accurate predictions on small data with a tabular foundation model (2025)	Prior Labs, University of Freiburg	Germany	—
13	Causal inference for time series (2023)	German Aerospace Center, German Aerospace Center (DLR), Max Planck Institute for Biogeochemistry	Germany, Spain	—
14	'Mendelian randomization': can genetic epidemiology contribute to understanding environmental determinants of disease?	University of Bristol	United Kingdom	—
15	Large Language Models as Simulated Economic Agents: What Can We Learn from Homo Silicus?	Fordham University, Massachusetts Institute of Technology	United States	—
16	Forecasting: theory and practice (2022)	Duke University, Kedge Business School, Monash University	Australia, Belgium, France	—
17	Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI (2020)	CaixaBank, Granada University, Sorbonne Université	France, Spain	—
18	Network analysis of multivariate data in psychological science (2021)	University of Amsterdam	Netherlands	—
19	Bayesian Data Analysis (1995)	Columbia University, Harvard University, Murdoch Children's Research Institute	Australia, United States	—
20	The Gaussian Graphical Model in Cross-Sectional and Time-Series Data (2018)	University of Amsterdam, University of Edinburgh	Netherlands, United Kingdom	—
21	On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms (2014)	Koç University, University of Pennsylvania	Turkey, United States	—
22	A Survey on Causal Inference (2021)	Alibaba Group, Purdue University, University of Georgia	United States	—
23	Studying Socioeconomic Status: Conceptual Problems and an Alternative Path Forward (2023)	University of California, Irvine Medical Center	United States	—
24	Less Data, More Knowledge: Building Next-Generation Semantic Communication Networks (2024)	Khalifa University	United Arab Emirates	—
25	Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable (2014)	Harvard University, University of Wisconsin	United States	—
26	Capturing Causal Complexity: Heuristics for Configurational Theorizing (2021)	City, University of London, London Business School, Louisiana State University	United Kingdom, United States	—
27	The Blessings of Multiple Causes	Columbia University	United States	—
28	EQS 6 Structural Equations Program Manual (2006)	Multivariate Software, Inc.	—	—
29	A Beginner's Guide to Structural Equation Modeling (2016)	The Ohio State University, University of Alabama	United States	—
30	Statistical inference links data and theory in network science (2022)	Central European University, Maastricht University, Universitat Rovira i Virgili	Austria, Netherlands, Spain	—

Showing the 30 most-cited of 444 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).

FOLLOW-UP WORK

The book of why: The new science of cause and effect

2018 · Basic Books, 2018 · 5,915 citations (GS)

Field-normalised: 2,333 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2018 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Mechanistic Interpretability for AI Safety – A Review	University of Amsterdam	Netherlands	—
2	Causal inference for time series	German Aerospace Center, German Aerospace Center (DLR), Max Planck Institute for Biogeochemistry	Germany, Spain	—
3	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	Aston Business School, Aston University, Banaras Hindu University	Denmark, India, Netherlands	Background
4	Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence	Centro Singular de Investigación en Tecnoloxías Intelixentes (CiTIUS), Universidade de Santiago de Compostela, Free University of Bozen-Bolzano, Galala University	Egypt, Italy, South Korea	—
5	Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation	Cornell University, TECNALIA, University of Granada	Austria, Spain, United States	—
6	Artificial Intelligence and Marketing: Pitfalls and Opportunities	Case Western Reserve University, Northwestern University, Penn State University	United States	Background
7	Data, Measurement, and Empirical Methods in the Science of Science	Northwestern University	United States	—
8	Capturing Causal Complexity: Heuristics for Configurational Theorizing	City, University of London, London Business School, Louisiana State University	United Kingdom, United States	—
9	A Beginner's Guide to Structural Equation Modeling	The Ohio State University, University of Alabama	United States	—
10	A survey on deep learning-based monocular spacecraft pose estimation: Current state, limitations and prospects	University of Luxembourg	Luxembourg	—
11	What Is Your Estimand? Defining the Target Quantity Connects Statistical Evidence to Theory	Dartmouth College, Princeton University	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
12	Generalizability of choice architecture interventions	Eötvös Loránd University, Microsoft Research, University College London	Canada, Hungary, United Kingdom	—
13	TabPFN: A Transformer That Solves Small Tabular Classification Problems in a Second	—	—	—
14	Unbiased Scene Graph Generation from Biased Training	Nanyang Technological University, Renmin University of China, Tsinghua University	China, Singapore	Influential
15	Finding the needle in a high-dimensional haystack: Canonical correlation analysis for neuroscientists	RWTH Aachen University, University College London, University of Pennsylvania	Germany, United Kingdom, United States	Methodology
16	A Picture is Worth A Thousand Numbers: Enabling LLMs Reason about Time Series via Visualization	Georgia Institute of Technology, Salesforce Research Asia	United States	—
17	Theory Is All You Need: AI, Human Cognition, and Causal Reasoning	University of Oxford	United Kingdom	—
18	Causability and explainability of artificial intelligence in medicine.	Institute of Pathology Medical University Graz, Medical University Graz, Medical University of Vienna	Austria	—
19	Causal Inference Meets Deep Learning: A Comprehensive Survey.	Xidian University	China	Background
20	Network Analysis of Psychopathology: Controversies and Challenges.	Harvard University	United States	—
21	Panel experiments and dynamic causal effects: A finite population perspective	Harvard Business School, Harvard University	United States	Methodology
22	Machine learning in information systems - a bibliographic review and open research issues	Goethe University Frankfurt	Germany	Background
23	How AI-Based Systems Can Induce Reflections: The Case of AI-Augmented Diagnostic Work	Goethe University	—	—
24	The neuroconnectionist research programme	Columbia University, Donders Institute, Harvard University	Canada, Germany, Netherlands	—
25	Large Language Models and the Reverse Turing Test	Salk Institute for Biological Studies	United States	—
26	Text Data Augmentation for Deep Learning.	Florida Atlantic University	United States	—
27	Discovering Causal Relations and Equations from Data	German Aerospace Center (DLR), Universitat de València, University of Potsdam	Germany, Spain	—
28	Disentangling User Interest and Conformity for Recommendation with Causal Embedding	Beijing National Research Center for Information Science and Technology & Tsinghua University, University of Hong Kong, University of	China	Background

No.	Citing paper	Citing institution(s)	Country	S2
		Science and Technology of China		
29	[Cross-Modal Causal Relational Reasoning for Event-Level Visual Question Answering]()	Sun Yat-sen University	China	—
30	[CLadder: Assessing Causal Reasoning in Language Models]()	Max Planck Institute for Intelligent Systems	Germany	**Methodology**

Showing the 30 most-cited of 181 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** Finding the needle in a high-dimensional haystack: Canonical correlation analysis for neuroscientists
>
> *"performed without applying the model to unseen observations or assessing the fundamental trueness of the effects, some authors recently called this modeling regime "retrodiction" (McElreath, 2015; Pearl and Mackenzie, 2018)."*

> **METHODOLOGY** Panel experiments and dynamic causal effects: A finite population perspective
>
> *"Our framework is also importantly distinct from earlier work by Robins (1986) and co-authors, that uses treatment paths for causal panel data analysis and solely focuses on providing super-population (or sampling-based) inference methods. In contrast, we avoid super-population arguments entirely and make our inference completely conditional on the potential outcomes. Avoiding super-populations arguments is often attractive in panel data applications. For example, a company only operates in a finite number of markets (e.g., states or cities within the United States) and can only conduct advertising or promotional experiments across these markets. Assuming that we can sample additional markets may be difficult to justify scientifically in such applications, despite its elegance as a modelling device.4 Overview of the paper: In Section 2, we define potential outcome panels, for which we formally define a series of dynamic causal estimands of interest. In Section 3, we provide a nonparametric estimator for our dynamic causal estimands, derive their finite sample properties, and provide finite population central limit theorems that we use for inference. In Section 4, we obtain the finite population limiting distributions of standard linear estimation methods for potential outcome panels, such as the unit fixed effects estimator and the two-way fixed effects estimator. In Section 5, we detail a simulation study, and in Section 6, we use our framework to reanalyze a panel experiment conducted by Andreoni and Samuelson (2006). The appendix collects all non-trivial technical proofs as well as additional simulations and empirical results."*

> **METHODOLOGY** CLadder: Assessing Causal Reasoning in Language Models
>
> *"...language are grounded in symbolic questions and ground truth answers : the latter are derived through an oracle causal inference engine (CI engine) [66], which abides by the rules of the causal inference approach described by Pearl [61], based on graphical models and structural causal models..."*

> **FOLLOW-UP WORK**
>
> ### [Direct and indirect effects]()
>
> 2022 · Probabilistic and causal inference: the works of Judea Pearl, 373-392, 2022 · 2,555 citations (GS)
>
> Field-normalised: 2,318 Semantic Scholar citations place it in the top 1% of Economics papers from 2022 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

Contribution 3

> ### Claim — Contribution 3
>
> *The researcher established foundational heuristics for intelligent search strategies in computer problem solving, a seminal contribution that has profoundly shaped the field of artificial intelligence.*

The researcher's core contribution rests on the seminal 1983 paper, 'Heuristics: intelligent search strategies for computer problem solving.' This work appears to define the theoretical and practical framework for using heuristics to guide search processes in complex computational problems. The titles indicate a focus on optimizing problem-solving efficiency through intelligent strategy selection rather than exhaustive search.

This line of work addresses the critical challenge of computational intractability in early artificial intelligence. By introducing structured heuristic approaches, the researcher provided a novel method for navigating large search spaces. The absence of follow-up papers by the same author suggests this single publication served as a definitive, standalone foundation for the concept, rather than part of an iterative series.

The significance of this contribution is evidenced by its extensive uptake, with over 5,500 citations. Notably, 98.9% of classified citations originate from independent researchers, indicating that the work has been widely adopted and built upon by the broader scientific community. This high degree of independent citation underscores the paper's role as a standard reference and its lasting impact on the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

Heuristics: intelligent search strategies for computer problem solving

1983 · Addison-Wesley Pub. Co., Inc., Reading, MA, 1983 · 5,567 citations (GS)

Field-normalised: 2,458 Semantic Scholar citations place it in the top 1% of Computer Science papers from 1983 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of California, Irvine Medical Center	United States	—	32
Stanford University	U.S.A	SCImago #18 · THE =5 · QS 3	31
Microsoft Research	United States	—	23
Massachusetts Institute of Technology	United States	SCImago #41 · THE 2 · QS 1	20
Harvard University	United States	SCImago #4 · THE =5 · QS 5	20
National University of Singapore	Singapore	SCImago #59 · THE 17 · QS 8	18
Columbia University	United States	SCImago #65 · THE 20 · QS =38	18
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	18
University of Cambridge	United Kingdom	SCImago #63 · THE =3 · QS 6	17
University of Toronto	Canada	SCImago #39 · THE 21 · QS 29	17
University of Washington	United States	SCImago #45 · THE 25 · QS 81	15
University of Science and Technology of China	China	SCImago #77 · THE 51 · QS =132	13
Google	United States	—	13
University of Amsterdam	Netherlands	SCImago #75 · THE =62 · QS 53	13
New York University	United States	SCImago #116 · THE =31 · QS 55	12

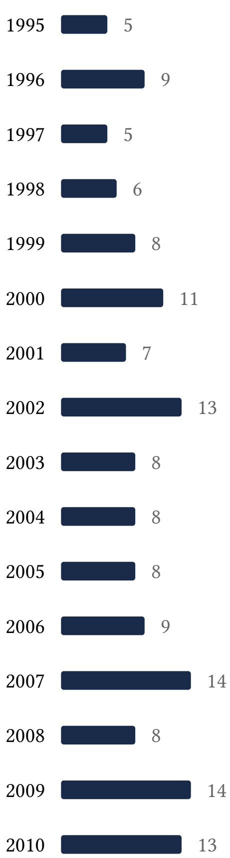
Geographic distribution of citing authors

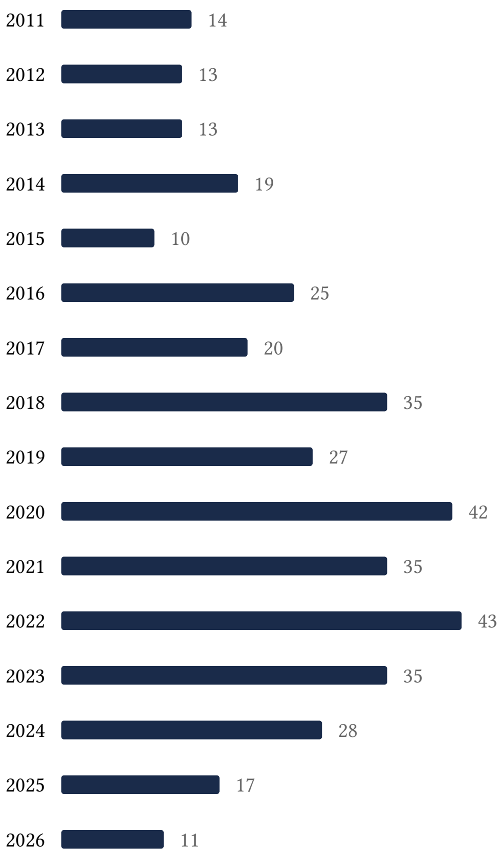
Country	Citing papers
United States	320
United Kingdom	82
Germany	52
China	47
Canada	45
Netherlands	43
Singapore	24
Australia	23
Italy	22
Switzerland	21
Israel	18
Spain	16

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.





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	Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference	364	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Causality	625	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Heuristics: intelligent search strategies for computer problem solving	0	8 CFR 204.5(h)(3)(v) — Criterion 5