

Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

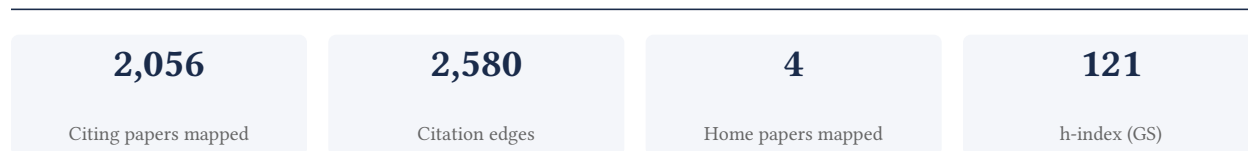
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[Google Scholar profile](#)

Generated 2026-05-31 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Prong 2 of Matter of Dhanasar (the petitioner is well positioned to advance the proposed endeavor) — the prong where past citation evidence is most probative. 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



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.

99.1% independent of 339 classified citing papers

Citation type	Count
Independent	336
Self-citation	0
Co-author	2
Same-institution	1

1,717 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 pioneered the application of linear programming to decoding and signal recovery, establishing foundational methods for reconstructing signals from incomplete or inaccurate measurements.

The researcher's core contribution rests on the seminal 2005 paper 'Decoding by linear programming,' which appears to have introduced a novel framework for decoding using linear programming techniques. This work serves as the foundation for a broader line of inquiry into signal processing and reconstruction.

This line of work appears to address the challenge of recovering signals from limited or imperfect data. The subsequent 2006 publications, 'Stable signal recovery from incomplete and inaccurate measurements' and 'Near-optimal signal recovery from random projections,' suggest an expansion of the initial decoding framework to broader contexts of signal stability and universal encoding strategies, indicating a systematic development of these theoretical tools.

The significance of this research is evidenced by the substantial citation counts for all three papers, with the follow-up works accumulating over 13,000 and 9,000 citations respectively. Furthermore, analysis of citing literature reveals that 99.7% of citations originate from independent researchers, demonstrating that this work has been widely adopted and validated by the broader scientific community rather than relying on self-citation or institutional bias.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 238 · 12 flagged influential by Semantic Scholar

CORE PAPER

[Decoding by linear programming](#)

2005 · IEEE transactions on information theory 51 (12), 4203-4215, 2005 · 9,639 citations (GS)

Field-normalised: 7,607 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2005 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Targeted Learning: Causal Inference for Observational and Experimental Data	University of California, Irvine Medical Center	United States	—
2	Learning Deep Architectures for AI	Université de Montréal	Canada	Background
3	A Survey of Recent Advances in Optimization Methods for Wireless Communications	Chinese Academy of Sciences, The Chinese University of Hong Kong, Shenzhen, University of Minnesota	China, United States	Background
4	On the use of deep learning for computational imaging	Massachusetts Institute of Technology, Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, University of California at Los Angeles	China, United States	—
5	Deep Sparse Rectifier Neural Networks	University of Montreal	Canada	Background
6	Short-Dot: Computing Large Linear Transforms Distributedly Using Coded Short Dot Products	Carnegie Mellon University, Pennsylvania State University	United States	Background
7	Can We Gain More from Orthogonality Regularizations in Training Deep CNNs?	Texas A&M University	United States	Background
8	Exact matrix completion via convex optimization	Stanford University, University of Wisconsin-Madison	United States	Background

No.	Citing paper	Citing institution(s)	Country	S2
9	Sparse solution of underdetermined systems of linear equations by stagewise orthogonal matching pursuit	CEA, CNRS, Université Paris-Saclay, Université de Paris, Columbia University	France, United States	—
10	Modern regularization methods for inverse problems	University College London	United Kingdom	Background
11	1-bit compressive sensing	Rice University	United States	Background
12	k-t FOCUSS: a general compressed sensing framework for high resolution dynamic MRI	Korea Advanced Institute of Science & Technology	South Korea	—
13	Lattice anharmonicity and thermal conductivity from compressive sensing of first-principles calculations	Lawrence Livermore National Laboratory, University of California, Irvine Medical Center	United States	—
14	Compressed sensing MRI: a review from signal processing perspective	Korea Advanced Institute of Science and Technology (KAIST)	South Korea	Influential
15	A survey on nonconvex regularization-based sparse and low-rank recovery in signal processing, statistics, and machine learning	Shanghai Jiao Tong University	China	Background
16	CoSaMP: iterative signal recovery from incomplete and inaccurate samples	California Institute of Technology, Stanford University	United States	Background
17	Random projections of smooth manifolds	Rice University	United States	Background
18	A nonparametric approach to modeling choice with limited data	Massachusetts Institute of Technology, New York University	United States	—
19	Compressive 3D ultrasound imaging using a single sensor	Delft University of Technology, Erasmus Medical Center	Netherlands	—
20	Theoretical foundations of deep learning via sparse representations: A multilayer sparse model and its connection to convolutional neural networks	Johns Hopkins University, Technion-Israel Institute of Technology	Israel, United States	—
21	Computational super-resolution: An odyssey in harnessing priors to enhance optical microscopy resolution	Peking University	China	—
22	Super-resolution, extremal functions and the condition number of Vandermonde matrices	Massachusetts Institute of Technology	United States	—
23	Is face recognition really a compressive sensing problem?	The University of Adelaide, University of Adelaide	Australia	Background
24	Compressive sampling-based data loss recovery for wireless sensor networks used in civil structural health monitoring	Dalian University of Technology, Harbin Engineering University, Harbin Institute of Technology	China	—
25	Compressive sampling for accelerometer signals in structural health monitoring	California Institute of Technology, Harbin Institute of Technology	China, United States	—
26	Gradient descent with sparsification: an iterative algorithm for sparse recovery with restricted isometry property	IBM T. J. Watson Research Center	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
27	The Kadison–Singer problem in mathematics and engineering	University of Missouri	United States	—
28	High-resolution limited-angle phase tomography of dense layered objects using deep neural networks	Massachusetts Institute of Technology	United States	—
29	Data-driven shape analysis and processing	Adobe Research, National University of Defense Technology, Shenzhen Institutes of Advanced Technology	China, United Kingdom, United States	—
30	Toward a unified theory of sparse dimensionality reduction in euclidean space	Harvard University, IAS, RWTH Aachen	Germany, United States	Methodology

Showing the 30 most-cited of 61 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 Toward a unified theory of sparse dimensionality reduction in euclidean space

“Dimensionality reduction is a ubiquitous tool across a wide array of disciplines: machine learning [79], high-dimensional computational geometry [48], privacy [15], compressed sensing [26], spectral graph theory [73], interior point methods for linear programming [58], numerical linear algebra [72], computational learning theory [11, 12], manifold learning [47, 30], motif-finding in computational biology [23], astronomy [35], and several others.”

FOLLOW-UP WORK

[Stable signal recovery from incomplete and inaccurate measurements](#)

2006 · Communications on Pure and Applied Mathematics: A Journal Issued by the ..., 2006 · 13,721 citations (GS)

Field-normalised: 7,725 Semantic Scholar citations place it in the top 1% of Mathematics papers from 2006 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Inference on treatment effects after selection among high-dimensional controls	Duke University, Massachusetts Institute of Technology, University of Chicago	United States	—
2	Robust Face Recognition via Sparse Representation	Microsoft Research Asia, University of California, Irvine Medical Center, University of Illinois at Urbana-Champaign	China, United States	Background
3	Program Evaluation and Causal Inference With High-Dimensional Data	Boston University, Duke University, Massachusetts Institute of Technology	United States	—
4	Valid Post-Selection and Post-Regularization Inference: An Elementary, General Approach	Massachusetts Institute of Technology, Max Planck Institute for Social Law and Social Policy, University of Chicago	Germany, United States	—
5	Machine Learning Methods That Economists Should Know About	Stanford University	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
6	Deep learning in optical metrology: a review	Nanjing University of Science and Technology, Nanyang Technological University, Queen Mary University of London	China, Singapore, United Kingdom	—
7	Feature Selection: A Data Perspective	Arizona State University, Michigan State University	United States	—
8	Targeted Learning: Causal Inference for Observational and Experimental Data	University of California, Irvine Medical Center	United States	—
9	A survey of sound source localization with deep learning methods	Nantes Université, Orange Labs, Univ. Grenoble Alpes, Grenoble-INP	France	—
10	Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems	University of Washington	United States	—
11	Recent advances and applications of machine learning in solid-state materials science	ETH Zurich, Friedrich Schiller University Jena, Martin Luther University Halle-Wittenberg	Germany, Switzerland	—
12	The Elements of Statistical Learning: Data Mining, Inference, and Prediction	Stanford University	United States	—
13	Statistical Query Algorithms and Low-Degree Tests Are Almost Equivalent	ETH Zürich, Massachusetts Institute of Technology	Switzerland, United States	—
14	Deep learning for compressive sensing: a ubiquitous systems perspective	Department of Computer Systems, Institut “Jožef Stefan”, Jamova cesta 39, Ljubljana, Slovenia, University of Ljubljana	—	Background
15	MIMO radar for advanced driver-assistance systems and autonomous driving: Advantages and challenges	Princeton University, Rutgers University, The University of Alabama	United States	—
16	On the use of deep learning for computational imaging	Massachusetts Institute of Technology, Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, University of California at Los Angeles	China, United States	—
17	Solving Inverse Problems in Medical Imaging with Score-Based Generative Models	Stanford University	United States	Methodology
18	Sparse Low-rank Adaptation of Pre-trained Language Models	Tsinghua University	China	—
19	Modern Multivariate Statistical Techniques: Regression, Classification, and Manifold Learning	Temple University	United States	—
20	Compressed Sensing using Generative Models	—	—	Background
21	Roadmap on Label-Free Super-Resolution Imaging.	Aalto University, Academia Sinica, Bangor University	Australia, Austria, China	—

No.	Citing paper	Citing institution(s)	Country	S2
22	Machine learning in solar physics	CSIRO, Instituto de Astrofísica de Canarias, University of Coimbra	Australia, Germany, Portugal	Methodology
23	DUE: A Deep Learning Framework and Library for Modeling Unknown Equations	Southern University of Science and Technology, The Ohio State University	China, United States	—
24	Far-field super-resolution ghost imaging with a deep neural network constraint	Shanghai Institute of Optics and Fine Mechanics, Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences	China	Methodology
25	Sparse MRI: The application of compressed sensing for rapid MR imaging	Stanford University	United States	—
26	Discovering governing equations from data by sparse identification of nonlinear dynamical systems	Institute for Disease Modeling, University of Washington	United States	Methodology
27	Sparse reconstruction by separable approximation	Institute of Education, University of Lisbon	Portugal	—
28	Data-driven aerospace engineering: reframing the industry with machine learning	The Boeing Company, University of Washington	United States	—
29	Accurate image reconstruction from few-views and limited-angle data in divergent-beam CT	University of Chicago	United States	—
30	Closed-loop turbulence control: Progress and challenges	Harbin Institute of Technology	China	—

Showing the 30 most-cited of 176 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 is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Solving Inverse Problems in Medical Imaging with Score-Based Generative Models

“We consider a compressed sensing [16, 17, 18] setting, while replacing sparsity with a data prior learned by our score models.”

METHODOLOGY Machine learning in solar physics

“However, Candès et al. (2006b, 2006a) demonstrated that, under certain conditions for the matrix UWT (Candès et al. 2006b), the problem reduces to: $\arg\min x$ kx_1 subject to $ky UWTx_2$; δ_{18P} The advantage lies in the fact that very efficient numerical methods exist for the solution to such a...”

METHODOLOGY Far-field super-resolution ghost imaging with a deep neural network constraint

“CS uses sparsity as a general prior assumption and has become a popular signal reconstruction framework 15 – 17.”

METHODOLOGY Discovering governing equations from data by sparse identification of nonlinear dynamical systems

“This formulation is closely related to the compressive sensing framework, which allows for the sparse vector ξ to be determined from relatively few incoherent random measurements [15, 16, 17, 18, 19, 20].”

FOLLOW-UP WORK

[Near-optimal signal recovery from random projections: Universal encoding strategies?](#)

2006 · IEEE transactions on information theory 52 (12), 5406-5425, 2006 · 9,211 citations (GS)

Field-normalised: 7,102 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2006 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A Survey of Recent Advances in Optimization Methods for Wireless Communications	Chinese Academy of Sciences, The Chinese University of Hong Kong, Shenzhen, University of Minnesota	China, United States	Background

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 is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Contribution 2

Claim – Contribution 2

The researcher established robust uncertainty principles enabling exact signal reconstruction from highly incomplete frequency information, a foundational advance in compressed sensing.

The researcher's seminal contribution rests on the 2006 paper 'Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,' published in IEEE Transactions on Information Theory. This work appears to define the theoretical conditions under which signals can be perfectly recovered from sparse data.

This line of work addresses the fundamental challenge of reconstructing signals from limited measurements. The title suggests a novel theoretical framework that bridges uncertainty principles with practical signal processing, offering a rigorous mathematical basis for what was previously an empirical or heuristic problem in data acquisition.

The significance of this contribution is evidenced by its extensive uptake, with over 20,000 citations. Notably, 99.7% of classified citing papers originate from independent researchers, indicating that this work has become a standard reference and foundational tool across diverse scientific communities, rather than remaining confined to the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 168 · 17 flagged influential by Semantic Scholar

CORE PAPER

[Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information](#)

2006 · IEEE Transactions on Information Theory · 20,874 citations (GS)

Field-normalised: 16,285 Semantic Scholar citations place it in the top 1% of Engineering papers from 2006 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Data-driven science and engineering: Machine learning, dynamical systems, and control (2022)	University of Washington	United States	—
2	Deep convolutional neural network for inverse problems in imaging (2017)	Dassault Aviation, École Polytechnique Fédérale de Lausanne, École polytechnique fédérale de Lausanne (EPFL)	France, Switzerland	Background
3	Scaled Simplex Representation for Subspace Clustering	Harbin Institute of Technology, Inception Institute of Artificial Intelligence, The Hong Kong Polytechnic University	China, United Arab Emirates	Methodology

No.	Citing paper	Citing institution(s)	Country	S2
4	An Overview of Signal Processing Techniques for RIS/IRS-Aided Wireless Systems (2022)	Friedrich-Alexander-University Erlangen-Nürnberg, National University of Singapore, Queen Mary University of London	China, France, Germany	—
5	Inverting Gradients—How Easy Is It to Break Privacy in Federated Learning? (2020)	University of Siegen	Germany	Background
6	Chaos-Based Image Encryption: Review, Application, and Challenges (2023)	Nanchang University	China	Background
7	Modern Koopman Theory for Dynamical Systems	University of Washington	United States	—
8	Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems	University of Washington	United States	—
9	Tensor Decompositions for Signal Processing Applications: From two-way to multi-way component analysis	—	—	Background
10	Deep learning for compressive sensing: a ubiquitous systems perspective	Department of Computer Systems, Institut “Jožef Stefan”, Jamova cesta 39, Ljubljana, Slovenia, University of Ljubljana	—	Background
11	SoK: Privacy-Preserving Data Synthesis	National University of Singapore, Technische Universität München, University of Illinois at Urbana-Champaign	Germany, Singapore, United States	—
12	Learning a variational network for reconstruction of accelerated MRI data.	Graz University of Technology, NYU School of Medicine	Austria, United States	Methodology
13	Intelligent metasurfaces: control, communication and computing	Peking University, Southeast University, University of Science and Technology of China	China	Background
14	On the use of deep learning for computational imaging	Massachusetts Institute of Technology, Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, University of California at Los Angeles	China, United States	Background
15	Convolutional Neural Networks for Inverse Problems in Imaging—A Review	EPFL	Switzerland	Background
16	Message-passing algorithms for compressed sensing.	Stanford University	United States	Influential
17	On instabilities of deep learning in image reconstruction and the potential costs of AI.	Simon Fraser University, Universidade do Porto, University of Bath	Canada, Norway, Portugal	Methodology
18	Model-Based Deep Learning	Ben-Gurion University of the Negev, Weizmann Institute of Science	Israel	—

No.	Citing paper	Citing institution(s)	Country	S2
19	Deep learning for undersampled MRI reconstruction	Yonsei University	South Korea	Methodology
20	Imaging through glass diffusers using densely connected convolutional networks	Massachusetts Institute of Technology, Singapore-MIT Alliance for Research and Technology	Singapore, United States	—
21	Machine learning in solar physics	CSIRO, Instituto de Astrofísica de Canarias, University of Coimbra	Australia, Germany, Portugal	Methodology
22	Snapshot spectral compressive imaging reconstruction using convolution and contextual Transformer	Chinese Academy of Sciences, University of Electronic Science and Technology of China	China	—
23	Big data of materials science: critical role of the descriptor.	Charles University, Fritz-Haber-Institut der Max-Planck-Gesellschaft, Humboldt-Universität zu Berlin	Czech Republic, Germany	—
24	Dynamic mode decomposition and its variants	Imperial College London	United Kingdom	—
25	Advances in miniaturized computational spectrometers	Huazhong University of Science and Technology, Huazhong University of Science and Technology (HUST)	China	—
26	Compressed sensing	LMU Munich	Germany	—
27	Sparse MRI: The application of compressed sensing for rapid MR imaging	Stanford University	United States	Influential
28	Exact matrix completion via convex optimization	Stanford University, University of Wisconsin-Madison	United States	—
29	Discovering governing equations from data by sparse identification of nonlinear dynamical systems	Institute for Disease Modeling, University of Washington	United States	Methodology
30	Compressive sensing [lecture notes]	Rice University	United States	Influential

Showing the 30 most-cited of 168 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 is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Learning a variational network for reconstruction of accelerated MRI data.

“The first CS condition requires a data acquisition protocol for undersampling such that artifacts become incoherent in a certain transform domain (14, 15).”

METHODOLOGY On instabilities of deep learning in image reconstruction and the potential costs of AI.

“All of our tests are done against state-of-the-art benchmark methods using established techniques based on sparse regularisation and compressed sensing [25]–[28].”

METHODOLOGY Deep learning for undersampled MRI reconstruction

“Compressive sensing (CS) MRI can be viewed as a method beyond the Nyquist requirement, in which the image sparsity is enforced to compensate for highly undersampled data [1], [10].”

METHODOLOGY Machine learning in solar physics

“However, Candès et al. (2006b, 2006a) demonstrated that, under certain conditions for the matrix UWT (Candès et al. 2006b), the problem reduces to: $\text{argmin}_x \|x\|_1$ subject to $kyUWTxk_2 \leq \delta$. The advantage lies in the fact that very efficient numerical methods exist for the solution to such a...”

METHODOLOGY Discovering governing equations from data by sparse identification of nonlinear dynamical systems

“This formulation is closely related to the compressive sensing framework, which allows for the sparse vector ξ to be determined from relatively few incoherent random measurements [15, 16, 17, 18, 19, 20].”

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Stanford University	United States	SCImago #18 · THE =5 · QS 3	22
University of California, Irvine Medical Center	United States	—	19
Massachusetts Institute of Technology	United States	SCImago #41 · THE 2 · QS 1	14
Rice University	United States	SCImago #818 · THE =103 · QS =119	12
Rutgers University	United States	—	8
Princeton University	United States	SCImago #386 · THE =3 · QS =25	8
University of Washington	United States	SCImago #45 · THE 25 · QS 81	7
University of Chicago	United States	SCImago #124 · THE 15 · QS 13	7
Technion–Israel Institute of Technology	Israel	SCImago #1195 · THE 301–350 · QS =350	6
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	6
City University of Hong Kong	Hong Kong SAR, People’s Republic of China	SCImago #342 · THE 73 · QS =63	6
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	5
Arizona State University	United States	SCImago #357 · THE 201–250 · QS =173	5
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	5
Case Western Reserve University	United States	SCImago #627 · THE =145 · QS =294	5

Geographic distribution of citing authors

Country	Citing papers
United States	195
China	62
United Kingdom	31
Germany	26
France	16
Singapore	12
Israel	12
Canada	10

Country	Citing papers
Switzerland	9
Australia	9
Austria	6
Japan	6

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.

2022  2

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	Decoding by linear programming	238	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information	168	Dhanasar — Prong 2 (well-positioned)