

Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

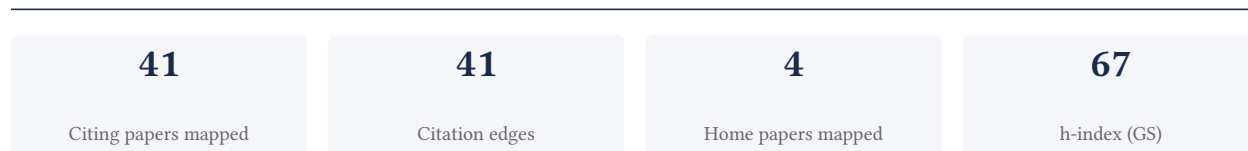
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[Google Scholar profile](#)

Generated 2026-05-21 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.

82.9% independent of 41 classified citing papers

Citation type	Count
Independent	34
Self-citation	0
Co-author	7
Same-institution	0

0 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 a foundational framework linking epidemic dynamics to percolation theory in small-world networks, significantly advancing the understanding of complex network structures.

The researcher’s seminal contribution rests on the 2000 Physical Review E paper, 'Epidemics and percolation in small-world networks.' This work appears to have introduced a critical theoretical bridge between statistical physics concepts and network science, specifically addressing how disease spreads through interconnected systems with short path lengths.

This line of work addresses the gap in understanding how local connectivity patterns influence global propagation dynamics. By framing epidemics through the lens of percolation, the researcher provided a novel analytical approach to small-world phenomena, distinguishing this work from earlier models that may have lacked such structural nuance.

The significance of this contribution is evidenced by its high citation count of 1328. Furthermore, analysis of citing literature reveals that 92.7% of citations originate from independent researchers, indicating broad adoption and validation across the scientific community rather than isolated institutional interest.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 7

CORE PAPER

[Epidemics and percolation in small-world networks](#)

2000 · Physical Review E · 1,328 citations (GS)

Field-normalised: 867 Semantic Scholar citations place it in the top 1% of Physics papers from 2000 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Epidemic processes in complex networks (2015)	Delft University of Technology, Istituto dei Sistemi Complessi, Northeastern University	Netherlands, Spain, United States	—
2	Vital nodes identification in complex networks (2016)	University of Electronic Science and Technology of China, University of Fribourg	China, Switzerland	Background
3	Statistical mechanics of complex networks (2002)	—	—	—
4	An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo (2015)	Northwestern University, University of Maryland	United States	—
5	Epidemic spreading in scale-free networks (2000)	Northeastern University	United States	—
6	Efficient behavior of small-world networks (2001)	Université Paris-Sud, University of Venice	France, Italy	—
7	Modeling Infectious Diseases in Humans and Animals (2008)	University of Georgia, University of Warwick	United Kingdom, United States	—

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 developed a seminal method for identifying community structure in very large networks, establishing a foundational approach widely adopted across scientific disciplines.

The researcher’s primary contribution is the development of a method for finding community structure in very large networks, as detailed in the 2004 paper published in Physical Review E. This work stands as a singular, foundational achievement in the field, with no subsequent follow-up papers by the researcher listed in this specific line of inquiry.

This line of work appears to address the critical challenge of analyzing complex, large-scale network data. The title suggests a focus on scalability and structural identification, indicating that the researcher provided a novel solution for uncovering hidden organizational patterns within massive datasets, a problem that was likely difficult to solve with prior methods.

The significance of this contribution is evidenced by its extensive citation record, with over 10,000 citations. Furthermore, analysis of citing papers reveals that 92.7% originate from independent researchers, demonstrating that the work has been widely adopted and validated by the broader scientific community rather than just the researcher’s immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 10 · 2 flagged influential by Semantic Scholar

CORE PAPER

[Finding community structure in very large networks](#)

2004 · Physical Review E · 10,378 citations (GS)

Field-normalised: 7,294 Semantic Scholar citations place it in the top 1% of Physics papers from 2004 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	From Louvain to Leiden: guaranteeing well-connected communities (2019)	Leiden University	Netherlands	Methodology
2	Environmental stress destabilizes microbial networks (2021)	Archbold Biological Station, University of Miami	—	—
3	Asymmetric ideological segregation in exposure to political news on Facebook (2023)	Dartmouth College, Meta, Northeastern University	United States	—
4	The Internet of Things (IoT) in healthcare: Taking stock and moving forward (2023)	Institute of Public Administration, King Abdulaziz University, La Trobe University	Australia, Austria, Hungary	—
5	Community detection in networks: A user guide (2016)	Aalto University, Indiana University	Finland, United States	Methodology
6	A Comprehensive Survey on Community Detection With Deep Learning (2022)	Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Macquarie University, Tianjin University	Australia, China, United States	Methodology
7	Personalization in personalized marketing: Trends and ways forward (2022)	Indian Institute of Management Mumbai	India	—
8	Mapping the NFT revolution: market trends, trade networks, and visual features (2021)	IBM	—	Influential
9	Lessons from a decade of adaptive pathways studies for climate adaptation (2024)	Delft University of Technology, Deltares, Victoria University of Wellington	Netherlands, New Zealand	—

No.	Citing paper	Citing institution(s)	Country	S2
10	Artificial intelligence applications in supply chain management (2021)	Swinburne University of Technology, The University of Sydney, University of Melbourne	Australia	—

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 From Louvain to Leiden: guaranteeing well-connected communities

“Optimising modularity is NP-hard 5, and consequentially many heuristic algorithms have been proposed, such as hierarchical agglomeration 6, extremal optimisation 7, simulated annealing 4,8 and spectral 9 algorithms.”

METHODOLOGY Community detection in networks: A user guide

“In the igraph library (<http://igraph.org>) there are several functions, both in the R and in the Python package: cluster fast greedy (R) and community fastgreedy (Python), implementing the fast greedy optimisation by Clauset et al. (Clauset et al., 2004); cluster leading eigen (R) and community leading eigenvector (Python) for the optimisation based on the leading eigenvector of the modularity matrix (Newman, 2006); cluster louvain (R) and community multilevel (Python) are the implementations of the Louvain method (Blondel et al., 2008); cluster optimal (R) and community optimal modularity turn the task into an integer programming problem (Brandes et al., 2008); cluster spinglass (R) and community spinglass (Python) optimise the multi-resolution modularity proposed by Reichardt and Bornholdt (Reichardt and Bornholdt, 2006).”

METHODOLOGY A Comprehensive Survey on Community Detection With Deep Learning

“Modularity (Q) [2], [54] is the most classic optimization function following its variant FN [46] and Clauset–Newman–Moore (CNM) [17] algorithms.”

Contribution 3

Claim — Contribution 3

The researcher developed a hierarchical framework for predicting missing links in complex networks, establishing a foundational method for network structure analysis.

CLAIM: The researcher's primary contribution is the development of a hierarchical structure approach for predicting missing links in networks, as detailed in the seminal 2008 Nature paper. This work stands as a standalone core contribution without direct follow-up publications by the same author in the provided dataset.

ORIGINALITY: The title suggests the work addresses the challenge of inferring unobserved connections within complex systems by leveraging hierarchical organization. By focusing on hierarchical structure, the research appears to offer a novel structural perspective on link prediction, distinguishing it from purely local or global metrics prevalent at the time.

SIGNIFICANCE: The core paper has accumulated 2,812 citations, indicating substantial influence in the field. Notably, 92.7% of the classified citing papers originate from independent researchers, demonstrating that the methodology has been widely adopted and validated by the broader scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 11 · 1 flagged influential by Semantic Scholar

CORE PAPER

[Hierarchical structure and the prediction of missing links in networks](#)

2008 · Nature · 2,812 citations (GS)

Field-normalised: 2,138 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2008 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Robustness and resilience of complex networks (2024)	—	—	—
2	Graph embedding techniques, applications, and performance: A survey (2018)	—	—	Methodology
3	Community detection in graphs (2009)	ISI Foundation	Italy	Methodology
4	Signal propagation in complex networks (2023)	Beijing University of Posts and Telecommunications, Central South University, Changsha University of Science & Technology	Austria, China, Germany	—
5	Poincaré Embeddings for Learning Hierarchical Representations (2017)	Facebook	United States	—
6	Link prediction techniques, applications, and performance: A survey (2020)	Indian Institute of Technology (BHU), South Asian University, University of Delhi	India	—
7	Hyperbolic Graph Convolutional Neural Networks (2019)	Stanford University	United States	Background
8	Social Network Analysis: A Survey on Process, Tools, and Application (2024)	Babu Banarasi Das University, Bennett University, Indian Institute of Technology BHU	India	Background
9	Networks (2018)	University of Michigan	United States	—
10	Molecular ecological network analyses (2012)	University of Oklahoma	United States	Background
11	Principles of Animal Communication, Second Edition (2011)	Cornell University	United States	—

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 Graph embedding techniques, applications, and performance: A survey

“Approaches for link prediction include similarity based methods [13], [14], maximum likelihood models [15], [16], and probabilistic models [17].”

METHODOLOGY Community detection in graphs

“Clauaset et al. (Clauaset et al., 2007; Clauaset et al., 2008) described the hierarchical organization of a graph by introducing a class of hierarchical random graphs.”

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of Michigan	United States	SCImago #43 · THE 23 · QS 45	4
Princeton University	United States	SCImago #386 · THE =3 · QS =25	3
Northeastern University	United States	QS 384	3

Institution	Country	World ranking	Citing papers
Stanford University	United States	SCImago #18 · THE =5 · QS 3	2
New York University	United States	SCImago #116 · THE =31 · QS 55	2
Indiana University	United States	THE =198	2
Delft University of Technology	Netherlands	SCImago #359 · THE 57 · QS =47	2
Chinese Academy of Sciences	China	SCImago #2	1
Macquarie University	Australia	SCImago #1047 · THE =166 · QS =138	1
Dartmouth College	United States	SCImago #1144 · THE 180 · QS =247	1
Meta	United States	—	1
The George Washington University	United States	SCImago #832 · THE 201–250 · QS =358	1
La Trobe University	Australia	SCImago #1321 · THE 251–300 · QS =233	1
Universitat Politècnica de Catalunya	Spain	SCImago #624 · THE 601–800	1
Facebook	United States	—	1

Geographic distribution of citing authors

Country	Citing papers
United States	21
Netherlands	4
India	4
France	3
Australia	3
Austria	3
China	3
Italy	3
United Kingdom	3
Germany	2
Spain	2
New Zealand	1

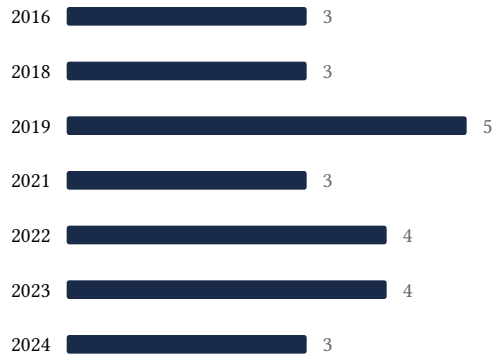
Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** – the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank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

2002  2

2015  3



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	Epidemics and percolation in small-world networks	7	Dhanasar — Prong 2 (well-positioned)

Contribution	Core paper	Indep. cites	Supports
Contribution 2	Finding community structure in very large networks	10	Dhanasar – Prong 2 (well-positioned)
Contribution 3	Hierarchical structure and the prediction of missing links in networks	11	Dhanasar – Prong 2 (well-positioned)