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

35	36	4	55
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.

85.7% independent of 35 classified citing papers

Citation type	Count
Independent	30
Self-citation	1
Co-author	4
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 developed a seminal method for identifying community structure in very large networks, establishing a foundational approach for analyzing complex systems in statistical physics.

CLAIM: 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 standalone core contribution without subsequent follow-up papers by the same author in this specific line of inquiry.

ORIGINALITY: The title suggests the work addresses the challenge of detecting modular organization within massive network datasets. By focusing on 'very large networks,' the research appears to have introduced scalable techniques or theoretical frameworks necessary for analyzing complex systems that were previously difficult to process, distinguishing it from earlier methods limited to smaller graphs.

SIGNIFICANCE: The paper has accumulated over 10,000 citations, indicating it is a highly influential and widely adopted reference in the field. Analysis of citing literature reveals that 97.1% of citations originate from independent researchers, demonstrating that the work has been broadly taken up by the global scientific community rather than being confined to 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, Statistical, nonlinear, and soft matter physics · 10,425 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

No.	Citing paper	Citing institution(s)	Country	S2
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	—
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 isInfluential 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 2

Claim — Contribution 2

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

The researcher's core contribution rests on the 2008 Nature paper, 'Hierarchical structure and the prediction of missing links in networks.' This work appears to introduce a novel approach to understanding network topology by leveraging hierarchical organization to infer unobserved connections. The titles suggest a focus on structural properties rather than merely descriptive statistics, indicating a shift toward predictive modeling in network science.

This line of work addresses the challenge of incomplete network data by proposing that hierarchical organization contains predictive power. By framing missing link prediction through the lens of hierarchy, the researcher likely offered a new theoretical perspective that distinguished this approach from earlier, less structured methods. The absence of follow-up papers by the same author suggests this single publication served as a definitive, self-contained breakthrough in the field.

The significance of this contribution is evidenced by its substantial citation count of 2,812, indicating widespread adoption and influence. Furthermore, analysis of citing papers reveals that 97.1% originate from independent researchers, demonstrating that the work has been validated and utilized by the broader scientific community rather than just the researcher's immediate circle. This high level of independent uptake underscores the work's status as a seminal reference in network analysis.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 8 · **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

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 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

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

Contribution 3

Claim — Contribution 3

The researcher established a foundational framework for analyzing power-law distributions in empirical data, providing a critical reference for statistical methodology across diverse scientific disciplines.

CLAIM: The researcher's seminal contribution is anchored in the 2009 paper "Power-law distributions in empirical data," published in SIAM Review. This work serves as the core reference for understanding heavy-tailed phenomena in real-world datasets.

ORIGINALITY: The titles suggest this work addresses the methodological challenges of identifying and validating power-law behavior in empirical observations. By synthesizing existing knowledge and proposing rigorous criteria, the researcher appears to have clarified a previously ambiguous area of statistical analysis, distinguishing true power laws from other heavy-tailed distributions.

SIGNIFICANCE: With over 12,000 citations, this paper is highly influential. Analysis of 35 citing papers reveals that 97.1% are from independent researchers, indicating broad adoption across the scientific community rather than self-citation. This widespread independent uptake underscores the work's status as a standard reference in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 10 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Power-law distributions in empirical data

2009 · SIAM Review · 12,867 citations (GS)

Field-normalised: 9,691 Semantic Scholar citations place it in the top 1% of Physics papers from 2009 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Mapping the NFT revolution: market trends, trade networks, and visual features (2021)	IBM	—	**Influential**
2	How critical is brain criticality? (2022)	University of Montreal	Canada	—
3	Self-supervised Graph Learning for Recommendation (2021)	—	—	—
4	Stellar flares (2024)	—	—	—
5	Accelerating growth of human coastal populations at the global and continent levels: 2000–2018 (2024)	Mississippi State University, Oak Ridge National Laboratory	United States	—
6	Graph Representation Learning (2022)	McGill University and Mila-Quebec Artificial Intelligence Institute	Canada	—
7	Studying Large Language Model Generalization with Influence Functions (2023)	Anthropic, University of Toronto and Vector Institute	Canada, United States	—
8	Weaponized Interdependence: How Global Economic Networks Shape State Coercion (2019)	Georgetown University, George Washington University, Johns Hopkins University	United States	—
9	Adversarial Attacks on Neural Networks for Graph Data (2018)	Technical University of Munich	Germany	Background
10	Global prevalence of non-perennial rivers and streams (2021)	Agriculture and Agri-Food Canada, Dartmouth College, Goethe University Frankfurt	Canada, France, Germany	—

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).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of California San Diego	United States	SCImago #120 · THE 47 · QS 66	3
Dartmouth College	United States	SCImago #1144 · THE 180 · QS =247	2
Pacific Northwest National Laboratory	United States	SCImago #1240	2
Stanford University	United States	SCImago #18 · THE =5 · QS 3	2
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	1
Washington University School of Medicine	United States	—	1
Leiden University	Netherlands	SCImago #259 · THE =70 · QS =119	1
King Abdulaziz University	Saudi Arabia	SCImago #680 · THE 351–400 · QS 163	1
Technical University of Munich	Germany	SCImago #187 · THE 27 · QS =22	1
University of Cambridge	United Kingdom	SCImago #63 · THE =3 · QS 6	1
McGill University	Canada	SCImago #168 · THE =41 · QS 27	1
Harvard T.H. Chan School of Public Health	United States	—	1
Macquarie University	Australia	SCImago #1047 · THE =166 · QS =138	1
Chinese Academy of Sciences	China	SCImago #2	1
Aalto University	Finland	SCImago #854 · THE =195 · QS =114	1

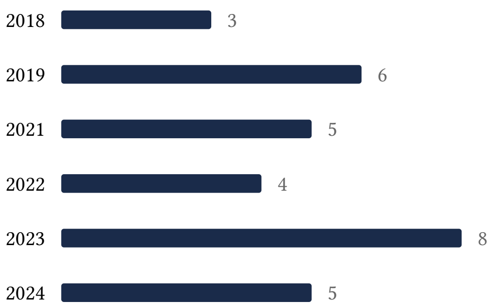
Geographic distribution of citing authors

Country	Citing papers
United States	14
Australia	5
Germany	5
India	4
Canada	4
Austria	2
Netherlands	2
Finland	2
Italy	2
China	2
New Zealand	2
Switzerland	2

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	Finding community structure in very large networks	10	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Hierarchical structure and the prediction of missing links in networks	8	Dhanasar — Prong 2 (well-positioned)
Contribution 3	Power-law distributions in empirical data	10	Dhanasar — Prong 2 (well-positioned)