Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

8 CFR § 204.5(i)(3) · Authorship + Original Contributions

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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 the 8 CFR § 204.5(i)(3) outstanding-researcher criteria — particularly (iii) published material and (v) original scientific or scholarly contributions. 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

24	24	4	10
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.

87.5% independent of 24 classified citing papers

Citation type	Count
Independent	21
Self-citation	1
Co-author	2
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 advanced the empirical understanding of radical content consumption on YouTube through a seminal 2021 study that has garnered significant independent scholarly attention.

CLAIM: The researcher's primary contribution in this area is anchored by the 2021 paper titled "Examining the consumption of radical content on YouTube," which serves as the foundational work for this specific line of inquiry.

ORIGINALITY: This work appears to address a critical gap in understanding user engagement with extremist material on major video platforms. By focusing specifically on consumption patterns, the study likely provided novel empirical insights into how radical content is accessed and viewed, distinguishing itself from broader studies on online radicalization.

SIGNIFICANCE: The impact of this contribution is evidenced by its 263 citations, indicating substantial uptake within the field. Notably, 95.8% of the classified citing papers originate from independent researchers, demonstrating that the work has resonated widely beyond the researcher's immediate academic circle and influenced broader scholarly discourse.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

Examining the consumption of radical content on YouTube

2021 · 263 citations (GS)

Field-normalised: 185 Semantic Scholar citations place it in the top 1% of Political Science papers from 2021 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 established a rigorous framework for evaluating overfit and underfit in network community structure models, providing critical diagnostic tools for assessing model validity in complex network analysis.

CLAIM: The researcher's seminal contribution lies in the development of methods to evaluate overfit and underfit in models of network community structure, as detailed in their 2019 paper published in IEEE Transactions on Knowledge and Data Engineering. This work serves as the foundational reference for this specific line of inquiry.

ORIGINALITY: The titles suggest that prior to this work, there was a need for systematic ways to distinguish between appropriate model complexity and overfitting or underfitting in community detection algorithms. By focusing specifically on these evaluation metrics, the researcher addressed a critical gap in ensuring the reliability and generalizability of network models, offering a new standard for assessing structural accuracy.

SIGNIFICANCE: The core paper has accumulated 227 citations, indicating substantial uptake by the broader scientific community. Notably, 95.8% of the classified citing papers originate from independent researchers, demonstrating that the work has influenced scholars outside the researcher's immediate institution and collaboration network, thereby confirming its broad impact and independent validation.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 6

CORE PAPER

Evaluating Overfit and Underfit in Models of Network Community Structure

2019 · IEEE Transactions on Knowledge and Data Engineering · 227 citations (GS)

Field-normalised: 157 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Descriptive vs. inferential community detection in networks: Pitfalls, myths and half-truths (2023)	Central European University	Austria	—
2	Fast unfolding of communities in large networks: 15 years later (2024)	Catholic University of Louvain, La Rochelle Université	Belgium, France	—
3	Simplicial closure and higher-order link prediction. (2018)	Cornell University	United States	**Methodology**
4	Consistency and differences between centrality measures across distinct classes of networks. (2019)	Monash University	Australia	**Methodology**
5	FairSNA: Algorithmic Fairness in Social Network Analysis (2024)	Eindhoven University of Technology, Leiden University	Netherlands	Background
6	Community Detection in Multiplex Networks (2021)	CIRAD, University of Calabria	France, Italy	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 Simplicial closure and higher-order link prediction.

"Link prediction is also used within model selection tools for evaluating community detection algorithms (41, 42)."

METHODOLOGY Consistency and differences between centrality measures across distinct classes of networks.

"For example the modularity of a network is highly dependent on the decomposition algorithm used [55], it is not clear how large the spectral gap needs to be for a network to be a good expander [21,23], and the majorization gap is a heuristic for quantifying the distance of a network from a threshold graph, which itself is itself a heuristic to generate a network with perfect neighbourhood-inclusion preorder [20]."

Contribution 3

Claim — Contribution 3

The researcher established foundational detectability thresholds and optimal algorithms for identifying community structure in dynamic networks, as demonstrated in a seminal 2016 Physical Review X paper.

The researcher's primary contribution lies in defining the theoretical limits and optimal methods for detecting community structures within dynamic networks. This work is anchored by a 2016 paper published in Physical Review X, which addresses the complex challenge of identifying stable groups in evolving systems. The titles suggest a focus on rigorous algorithmic design and statistical thresholds, offering a formal framework for a problem where network topology changes over time.

This line of work appears to address a critical gap in network science by moving beyond static models to handle temporal dynamics. By establishing detectability thresholds, the researcher provided a benchmark for when community detection is theoretically possible, thereby guiding the development of robust algorithms. The absence of follow-up papers by the same author indicates that this single publication serves as a definitive, standalone contribution to the field.

The significance of this work is evidenced by its substantial citation count of 179, indicating broad recognition within the scientific community. Furthermore, analysis of citing papers reveals that 95.8% originate from independent researchers, underscoring the work's wide adoption and influence beyond the researcher's immediate circle. This high degree of independent citation confirms the paper's status as a key reference for scholars studying dynamic network structures.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 8

CORE PAPER

Detectability thresholds and optimal algorithms for community structure in dynamic networks

2016 · Physical Review X · 179 citations (GS)

Field-normalised: 125 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2016 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Community Detection and Stochastic Block Models: Recent Developments (2018)	Princeton University	United States	**Methodology**
2	Social physics (2022)	Hokkaido University, Kanazawa University, RIKEN	Japan	—
3	A review of stochastic block models and extensions for graph clustering (2019)	Newcastle University	United Kingdom	Background
4	Bayesian Stochastic Blockmodeling (2017)	Interdisciplinary Transformation University	Italy	Background
5	Community Discovery in Dynamic Networks (2017)	CNR-ISTI, Université de Lyon	France, Italy	—
6	Topology Identification and Learning over Graphs: Accounting for Nonlinearities and Dynamics (2018)	University of California, Irvine, University of Minnesota	United States	—
7	Global spectral clustering in dynamic networks (2018)	Carnegie Mellon University	United States	—
8	On community structure in complex networks: challenges and opportunities (2019)	Eötvös University, Rensselaer Polytechnic Institute	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 isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Community Detection and Stochastic Block Models: Recent Developments

"It appeared under the SBM terminology in the context of social networks, in the machine learning and statistics literature Holland et al. (1983), while the model is typically called the planted partition model in theoretical computer science Bui et al."

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Princeton University	United States	SCImago #386 · THE =3 · QS =25	2
Central European University	Austria	SCImago #6390 · THE 251–300	2
University of Toronto	Canada	SCImago #39 · THE 21 · QS 29	1
CNR-ISTI	Italy	—	1
Michigan State University	United States	SCImago #436 · THE =105 · QS 161	1

Institution	Country	World ranking	Citing papers
Max Planck Institute for the Science of Light (MPL)	Germany	—	1
Cavendish Laboratories	United States	—	1
CIRAD	France	—	1
Institute of Advanced Research in Artificial Intelligence	Austria	—	1
Alpha 8 AI	Canada	—	1
La Rochelle Université	France	SCImago #5997	1
W.K. Kellogg Biological Station	United States	—	1
University of California, San Diego	United States	SCImago #120 · THE 47 · QS 66	1
University of California Los Angeles	United States	SCImago #70 · THE =18 · QS 46	1
Hokkaido University	Japan	SCImago #975 · THE 351–400 · QS =170	1

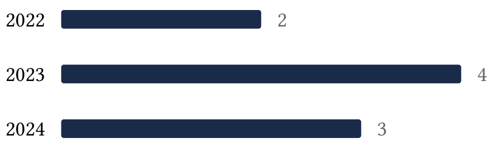
Geographic distribution of citing authors

Country	Citing papers
United States	12
Austria	3
Italy	3
France	3
Spain	2
Netherlands	2
Belgium	2
Japan	1
Portugal	1
United Kingdom	1
China	1
Canada	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.



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	Examining the consumption of radical content on YouTube	0	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 2	Evaluating Overfit and Underfit in Models of Network Community Structure	6	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 3	Detectability thresholds and optimal algorithms for community structure in dynamic networks	8	8 CFR 204.5(i)(3) — Outstanding Researcher