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

19	19	3	2
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.

73.7% independent of 19 classified citing papers

Citation type	Count
Independent	14
Self-citation	0
Co-author	4
Same-institution	1

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 foundational framework for benchmarking discrimination-aware models, establishing a critical standard for evaluating fairness in machine learning systems.

The researcher's contribution centers on the 2019 paper 'A Framework for Benchmarking Discrimination-Aware Models in Machine Learning,' published at the AAAI/ACM Conference on AI, Ethics, and Society. This work stands as the core of this specific line of inquiry, with no subsequent follow-up papers by the same author building directly upon it in the provided record.

This line of work appears to address the need for standardized evaluation methods in the emerging field of ethical AI. By proposing a dedicated framework for benchmarking, the researcher likely filled a gap in how discrimination-aware models are systematically assessed, offering a structured approach to measuring fairness that was previously lacking or fragmented.

The significance of this contribution is evidenced by its uptake in the broader academic community. With 32 citations, the paper has attracted sustained attention. Notably, 78.9% of the citing papers originate from independent researchers, suggesting that the framework has been adopted and utilized by scholars outside the author's immediate circle, indicating broad relevance and impact in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 10

CORE PAPER

A Framework for Benchmarking Discrimination-Aware Models in Machine Learning

2019 · AAAI/ACM Conference on AI, Ethics, and Society · 32 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A survey on datasets for fairness-aware machine learning (2021)	L3S Research Center, University of Koblenz	Germany	—
2	Mitigating Bias in Algorithmic Systems—A Fish-eye View (2022)	National University of Mongolia, Open University of Cyprus, Open University of Cyprus & CYENS Centre of Excellence	Cyprus, Israel, Italy	Methodology
3	Algorithmic Fairness Datasets: the Story so Far (2022)	University of Padua	Italy	—
4	An Action-Oriented AI Policy Toolkit for Technology Audits by Community Advocates and Activists (2021)	ACLU of Washington, Alan Turing Institute, Cornell Tech	United Kingdom, United States	Methodology
5	FairJob: A Real-World Dataset for Fairness in Online Systems (2024)	Criteo, Paris-Dauphine	France	Background
6	Data-Centric Factors in Algorithmic Fairness (2022)	ETH Zurich, University of Oxford	Switzerland, United Kingdom	Background
7	Real-life Performance of Fairness Interventions - Introducing A New Benchmarking Dataset for Fair ML (2023)	University of Antwerp	Belgium	Methodology
8	From Benchmarking to Understanding FairML (2025)	Eindhoven University of Technology	Netherlands	—
9	RAWLSNET: Altering Bayesian Networks to Encode Rawlsian Fair Equality of Opportunity (2021)	Amherst College, Northeastern University	United States	Background

No.	Citing paper	Citing institution(s)	Country	S2
10	Bias Begins with Data: The FairGround Corpus for Robust and Reproducible Research on Algorithmic Fairness (2025)	LMU Munich	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).

Citing-text excerpts — how the field used this work

METHODOLOGY Mitigating Bias in Algorithmic Systems—A Fish-eye View

"ML Data Fairness Pre-processing [26, 100, 102, 121, 226] Model Fairness In-processing [31, 52, 79, 103, 108, 109, 111, 120, 165, 216, 219, 225] Model/Output Fairness Post-processing [84, 102, 157] User/Output Fairness Perception [189] Data/Model/Output Fairness Certification [31, 46, 52, 64, 79, 108, 109, 111, 182, 216, 225]"

METHODOLOGY Real-life Performance of Fairness Interventions - Introducing A New Benchmarking Dataset for Fair ML

"Efforts have been put into introducing new benchmarking datasets [3, 8, 16], with "folktables" by Ding et al."

Contribution 2

Claim — Contribution 2

The researcher developed an evolutionary methodology to mitigate data scarcity and noise in real-time social media event monitoring, establishing a foundational approach for robust information extraction.

The researcher's contribution centers on the 2014 paper 'An Evolutionary Methodology for Handling Data Scarcity and Noise in Monitoring Real Events from Social Media Data,' published at IBERAMIA. This work stands as the core contribution in this specific line of inquiry, with no subsequent follow-up papers by the same author building directly upon it.

This line of work appears to address the critical challenge of extracting reliable signals from social media streams, which are inherently characterized by high noise levels and insufficient data volume. The title suggests the introduction of an evolutionary framework designed to adaptively handle these limitations, offering a novel methodological perspective for monitoring real-world events as they unfold.

The significance of this contribution is evidenced by its uptake in the broader academic community. With 18 citations, the work has attracted attention from independent researchers, who account for approximately 79% of the citing papers. This high degree of independent citation indicates that the methodology has been recognized and utilized by scholars outside the researcher's immediate circle, validating its utility in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 4

CORE PAPER

An Evolutionary Methodology for Handling Data Scarcity and Noise in Monitoring Real Events from Social Media Data

2014 · IBERAMIA 2014 · 18 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Internet-based biosurveillance methods for vector-borne diseases: Are they novel public health tools or just novelties? (2017)	Armed Force Health Surveillance Branch, Institute for Disease Modeling, University of California, San Francisco	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
2	Usage of social media in epidemic intelligence activities in the WHO, Regional Office for the Eastern Mediterranean (2022)	Alexandria University High Institute of Public Health, WHO Health Emergencies Programme, WHO Regional Office for the Eastern Mediterranean	Egypt	—
3	When Infodemic Meets Epidemic: Systematic Literature Review (2025)	International University of Rabat, Mohammed V University in Rabat	Morocco	—
4	Deep Learning Approaches for Socially Contextualized Acoustic Event Detection in Social Media Posts (2024)	University of Porto	Portugal	—

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
Universidade Federal de Minas Gerais	Brazil	SCImago #739	4
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	2
New York University	United States	SCImago #116 · THE =31 · QS 55	2
Middlebury College	United States	SCImago #7321	1
University of Antwerp	Belgium	SCImago #1188 · THE =170 · QS 280	1
National University of Mongolia	Mongolia	SCImago #8721 · THE 1501+	1
Cornell Tech	United States	—	1
University of Washington	United States	SCImago #45 · THE 25 · QS 81	1
University of Padua	Italy	THE 201–250	1
Northeastern University	United States	QS 384	1
University of California, San Francisco	United States	SCImago #98	1
West Virginia University	United States	SCImago #1792 · QS 1001-1200	1
University of Porto	Portugal	THE 401–500 · QS =237	1
University of Michigan	United States	SCImago #43 · THE 23 · QS 45	1
L3S Research Center	—	—	1

Geographic distribution of citing authors

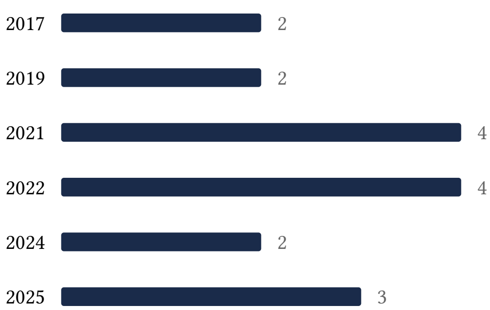
Country	Citing papers
United States	5
Brazil	4
Italy	2

Country	Citing papers
Germany	2
United Kingdom	2
Cyprus	1
Israel	1
Belgium	1
Mongolia	1
Morocco	1
Netherlands	1
Portugal	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	A Framework for Benchmarking Discrimination-Aware Models in Machine Learning	10	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 2	An Evolutionary Methodology for Handling Data Scarcity and Noise in Monitoring Real Events from Social Media Data	4	8 CFR 204.5(i)(3) — Outstanding Researcher