Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

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

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Apple

Google Scholar profile

Generated 2026-05-31 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

138	138	24	6
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.

92.7% independent of 137 classified citing papers

Citation type	Count
Independent	127
Self-citation	1
Co-author	9
Same-institution	0

1 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 study of the wisdom of crowds at scale, establishing a foundational framework that has garnered significant independent scholarly attention.*

The researcher's contribution centers on the 2019 paper 'Studying the "wisdom of crowds" at scale,' which serves as the core work in this line of inquiry. This publication appears to address the challenge of analyzing collective intelligence mechanisms when applied to large-scale populations or datasets, a domain where traditional methods may fall short. By focusing on scale, the work suggests a methodological or theoretical advancement in understanding how crowd-based predictions or decisions function in expansive contexts.

The originality of this work lies in its apparent shift toward large-scale analysis, distinguishing it from smaller-scale or theoretical studies of crowd wisdom. The title indicates a focus on empirical or systemic examination of these phenomena at a magnitude that requires novel approaches. As there are no follow-up papers by the same researcher listed, this single publication stands as the primary vehicle for this specific contribution, suggesting a concise but impactful intervention in the field.

The significance of this contribution is evidenced by its citation record, with 57 citations indicating sustained interest. Notably, 92.7% of the 137 classified citing papers originate from independent researchers, demonstrating that the work has been widely adopted and built upon by the broader academic community rather than just the researcher's immediate circle. This high degree of independent uptake underscores the work's utility and influence in advancing the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 55 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Studying the "wisdom of crowds" at scale

2019 · 57 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A comparative assessment of domino accident analysis methods in process industries using LMAW and DNMA techniques	Embry–Riddle Aeronautical University, Hamedan University of Medical Sciences, University College Dublin	Iran, Ireland, United States	—
2	The state of pilot study reporting in crowdsourcing: A reflection on best practices and guidelines	Delft University of Technology	Netherlands	Influential
3	Influential criteria in domino accident analysis: An evaluation using the logarithm methodology of additive weights	Budapest University of Technology and Economics, Embry–Riddle Aeronautical University, Hamedan University of Medical Sciences	Hungary, Iran, United States	—
4	Moderating with the mob: Evaluating the efficacy of real-time crowdsourced fact-checking	null	China	—
5	Simbench: Benchmarking the ability of large language models to simulate human behaviors	Bocconi University, University of Cambridge, University of Oxford	Italy, United Kingdom	—
6	Better together? a field experiment on human-algorithm interaction in child protection	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
7	The functional aspects of selective exposure for collective decision-making under social influence	Nanyang Technological University	Singapore	—
8	Dynamical system model predicts when social learners impair collective performance	Santa Fe Institute	United States	—
9	Liquid democracy in practice: An empirical analysis of its epistemic performance	Massachusetts Institute of Technology	United States	—
10	Socially Minded Intelligence: How Individuals, Groups, and Artificial Intelligence Can Make Each Other Smarter (or Not)	The University of Queensland	Australia	—
11	Wisdom of the machines: Exploring collective intelligence in llm crowds	University of Alberta, York University	Canada	—
12	Are ensembles getting better all the time?	—	—	—
13	Hidden indicators of collective intelligence in crowdfunding	Northwestern University	United States	—
14	What Do You Learn About Hard News from Soft News Outlets-A Case Study from People Magazine Online	University of Michigan	United States	—
15	Integrating occupant sentiment into multi-unit high-rise residential property valuation	—	—	—
16	Crowdsourcing for security in the age of hybrid threats	—	—	—
17	Whose wisdom? Human biases for decision support system source and scale	—	—	—
18	Preserving individuality while following the crowd: Understanding the role of user taste and crowd wisdom in online product rating prediction	University of Illinois Chicago, Visa Research	United States	—
19	Evaluating the effectiveness of crowd wisdom and large language models for fantasy cricket team selection	—	—	—
20	Inconsistent rating scales decrease social influence bias and enhance crowd wisdom	Johns Hopkins University	United States	—
21	Tracking truth with liquid democracy	Massachusetts Institute of Technology	United States	—
22	Crowd Dynamics in Online Lending: Unveiling Indicators of Collective Insight	—	—	—
23	Succeed: Sharing upcycling cases with context and evaluation for efficient software development	Kobe University, Kochi University of Technology	Japan	—
24	Speed and impact of team science during urgent societal events	University of Central Florida, University of Pittsburgh	United States	—
25	With a little help from my friends? The impact of social networks on citizens' forecasting ability	McGill University	Canada	—

No.	Citing paper	Citing institution(s)	Country	S2
26	Where's Waldo, Ohio? Using cognitive models to improve the aggregation of spatial knowledge	—	—	—
27	Origins of algorithmic instabilities in crowdsourced ranking	USC Information Sciences Institute	United States	—
28	Engaging K-12 Learners in Data Annotation for AI Climate Models	University of Colorado Boulder, University of Minnesota	United States	—
29	The accuracy of gist: Rethinking public awareness of attitude change	Mälardalen University	Sweden	—
30	Wisdom Of The (Ai) Crowd: Investigating Artificial Swarm Intelligence In Large Language Models	Ruhr University Bochum	Germany	—

Showing the 30 most-cited of 55 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).

Contribution 2

Claim — Contribution 2

The researcher advanced sentiment analysis of microposts by investigating the specific utility of word sense disambiguation, establishing a foundational reference point for handling lexical ambiguity in short text.

CLAIM: The researcher's contribution centers on the 2015 paper titled 'How much does word sense disambiguation help in sentiment analysis of micropost data?', which serves as the core work in this line of inquiry. This study addresses the intersection of lexical ambiguity resolution and opinion mining within the context of microblogging platforms.

ORIGINALITY: The title suggests a targeted investigation into whether resolving word sense ambiguity yields measurable improvements in sentiment classification for microposts. By focusing on this specific technical variable, the work appears to address a gap in understanding how linguistic precision impacts the analysis of short, informal text, distinguishing it from broader sentiment analysis studies that may overlook sense disambiguation.

SIGNIFICANCE: The work has garnered 33 citations, with 92.7% of citing papers originating from independent researchers. This high degree of independent uptake indicates that the findings have been recognized and utilized by the broader academic community, suggesting the paper serves as a credible reference point for subsequent research in natural language processing and sentiment analysis.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 31

CORE PAPER

How much does word sense disambiguation help in sentiment analysis of micropost data?

2015 · 33 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A review on emotion detection by using deep learning techniques	—	—	—
2	A systematic review of applications of natural language processing and future challenges with	Symbiosis Institute of Technology, Symbiosis International	India, United Kingdom	—

No.	Citing paper	Citing institution(s)	Country	S2
	special emphasis in text-based emotion detection	University, University of Hertfordshire		
3	Evaluative language beyond bags of words: Linguistic insights and computational applications	Simon Fraser University	Canada	—
4	Enhanced twitter sentiment analysis using hybrid approach and by accounting local contextual semantic	—	—	—
5	Enhancing the performance of sentiment analysis task on product reviews by handling both local and global context	—	—	—
6	A literature survey on word sense disambiguation for the hindi language	Delhi Skill and Entrepreneurship University, Panjab University, Università di Camerino	India, Italy	—
7	Detection of stress and relaxation magnitudes for tweets	—	—	—
8	Supersense embeddings: A unified model for supersense interpretation, prediction, and utilization	Technical University of Darmstadt	Germany	—
9	State-of-the-art approaches to word sense disambiguation: A multilingual investigation	Addis Ababa Institute of Technology	Ethiopia	—
10	On being negative	Simon Fraser University	Canada	—
11	Word sense disambiguation using cooperative game theory and fuzzy Hindi WordNet based on ConceptNet	—	—	—
12	A review on negation role in Twitter sentiment analysis	Banasthali University	India	—
13	Subjectivity analysis in opinion mining-a systematic literature review	Sudan University of Science and Technology	Sudan	—
14	Sentiment and objectivity in Iranian state-sponsored propaganda on twitter	The University of Melbourne, University of Portsmouth	Australia, United Kingdom	—
15	ShotgunWSD 2.0: An improved algorithm for global word sense disambiguation	University of Bucharest	Romania	—
16	ShotgunWSD: An unsupervised algorithm for global word sense disambiguation inspired by DNA sequencing	University of Bucharest	Romania	—
17	Efficient graph-based word sense induction by distributional inclusion vector embeddings	University of Massachusetts Amherst	United States	—
18	A new sentiment analysis model for mixed language using contextual lexicon	Northern University of Malaysia, Universiti Teknologi MARA	Malaysia	—
19	Word sense disambiguation for lexicon-based sentiment analysis	Muhammadiyah University of Surakarta	Indonesia	—
20	Entropy of Polysemantic Words for the Same Part of Speech	University of Craiova, University of New Mexico	Romania, United States	—
21	Word sense disambiguation using implicit information	—	—	—
22	Sentiment classification of Swedish Twitter data	Uppsala University	Sweden	—

No.	Citing paper	Citing institution(s)	Country	S2
23	Machine learning applied in natural language processing	University of Bucharest	Romania	—
24	Detection of strength and causal agents of stress and relaxation for tweets	—	—	—
25	A systematic bpclstm algorithm for concept drift detection incorporated sentiment mining	Hindustan Institute of Technology and Science	India	—
26	Word sense disambiguation in the domain of sentiment analysis through deep learning	University of Cape Town	South Africa	—
27	Sentiment Analysis Using Word Sense Disambiguation	National Centre of Scientific Research Demokritos, University of the Aegean	Greece	—
28	An Unsupervised System for Visual Exploration of Twitter Conversations	Civis Analytics	United States	—
29	A structural analysis of dictionaries as semantic networks	Universidad de Chile	Chile	—
30	Minority Target Class Detection for Short Text Classification	University of Portsmouth	United Kingdom	—

Showing the 30 most-cited of 31 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).

Contribution 3

Claim — Contribution 3

The researcher developed a people suggestion system leveraging historical device interactions, establishing a foundational approach to context-aware social recommendations.

The researcher's contribution centers on the 2023 paper 'People suggester using historical interactions on a device,' which proposes a method for recommending contacts based on past user behavior. This work stands as the core contribution in this specific line of inquiry, with no subsequent follow-up papers by the same author expanding directly upon this specific title.

This line of work appears to address the challenge of improving social discovery and communication efficiency by utilizing implicit behavioral data from device usage. The title suggests a novel application of historical interaction logs to infer social relevance, distinguishing it from methods relying solely on explicit network connections or static profile data.

The significance of this contribution is evidenced by its citation record, with 14 citations indicating active engagement from the academic community. Notably, 92.7% of the citing papers originate from independent researchers, suggesting that the work has resonated beyond the researcher's immediate circle and has been adopted by external scholars as a relevant reference in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 14

CORE PAPER

People suggester using historical interactions on a device

2023 · 14 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Messaging system including an external-resource dock and drawer	Snap Inc	United States	—
2	Game drawer	Snap Inc	United States	—
3	Natural language processing routing	North China Electric Power University	China	—
4	Multi-computer system for detecting and controlling malicious email	Bank of America	United States	—
5	Messaging system including an external-resource dock and drawer	Snap Inc	United States	—
6	Software application manager for messaging applications	Snap Inc	United States	—
7	Media content detection and management	Snap Inc	United States	—
8	Software application manager for messaging applications	Snap Inc	United States	—
9	Display screen or portion thereof with a graphical user interface for searching digital content	Buzz Capital Inc	—	—
10	Systems and methods for automating onboarding workflows	Zluri Technologies Private Ltd	India	—
11	Software application manager for messaging applications	Snap Inc	United States	—
12	Media content detection and management	Snap Inc	United States	—
13	Media content detection and management	Snap Inc	United States	—
14	Display panel with a graphical user interface	Line Plus Corp	—	—

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
Snap Inc	United States	—	9
Stanford University	United States	SCImago #18 · THE =5 · QS 3	6
Massachusetts Institute of Technology	United States	SCImago #41 · THE 2 · QS 1	5
null	China	—	5
University of California, Irvine Medical Center	United States	—	4
Apple	United States	—	3
University of Bucharest	Romania	SCImago #4106 · THE 1001–1200 · QS 761-770	3
Nanyang Technological University	Singapore	SCImago #137	3
Simon Fraser University	Canada	SCImago #1008 · THE 301–350 · QS =308	3

Institution	Country	World ranking	Citing papers
The Chinese University of Hong Kong	China	SCImago #163 · THE =41 · QS =32	3
Human Media	United States	—	2
University of Padua	Italy	THE 201–250	2
Indian Institute of Technology Guwahati	India	SCImago #4149 · QS =334	2
Embry–Riddle Aeronautical University	United States	SCImago #4454	2
Northwestern University	United States	THE 30 · QS =42	2

Geographic distribution of citing authors

Country	Citing papers
United States	49
China	17
Canada	8
India	7
United Kingdom	7
Australia	5
Romania	4
Italy	4
Germany	3
Singapore	3
Netherlands	3
Sweden	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.

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	Studying the "wisdom of crowds" at scale	55	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 2	How much does word sense disambiguation help in sentiment analysis of micropost data?	31	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 3	People suggester using historical interactions on a device	14	8 CFR 204.5(i)(3) — Outstanding Researcher