

# Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

**Yi-Ou Li**

UCSF

[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

37	37	5	17
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.

**67.6% independent** of 37 classified citing papers

Citation type	Count
Independent	25
Self-citation	0
Co-author	12
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 method for estimating the number of independent components in fMRI data, a foundational technique widely adopted by independent scholars in neuroimaging.*

CLAIM: The researcher’s primary contribution is the development of a method for estimating the number of independent components in functional magnetic resonance imaging data, as detailed in their 2007 paper published in Human Brain Mapping. This work stands as a seminal piece in the field, with no subsequent follow-up papers by the same author listed in this specific line of inquiry.

ORIGINALITY: The title suggests the work addresses a critical methodological challenge in fMRI analysis: determining the appropriate dimensionality or number of independent sources within complex brain imaging data. By providing a framework for this estimation, the researcher appears to have offered a novel solution to a problem that likely lacked standardized approaches at the time, enabling more accurate decomposition of neural signals.

SIGNIFICANCE: The impact of this contribution is evidenced by its substantial citation count of 1,059, indicating widespread recognition and utility within the scientific community. Furthermore, analysis of citing papers reveals that 100% of the classified citations originate from independent researchers, demonstrating that the method has been broadly adopted and validated by the wider field rather than being confined to the researcher’s immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 3

### CORE PAPER

#### [Estimating the number of independent components for functional magnetic resonance imaging data](#)

2007 · Human Brain Mapping · 1,059 citations (GS)

Field-normalised: 924 Semantic Scholar citations place it in the top 1% of Medicine papers from 2007 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review</a> (2018)	University of Bern, University of Geneva	Switzerland	—
2	<a href="#">Functional MRI in major depressive disorder: A review of findings, limitations, and future prospects</a> (2022)	Eindhoven University of Technology, Epilepsy Centre Kempenhaeghe, Philips Research	Netherlands	—
3	<a href="#">Reliable intrinsic connectivity networks: test-retest evaluation using ICA and dual regression approach</a> (2010)	New York 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 isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

## Contribution 2

### Claim – Contribution 2

*The researcher developed a canonical correlation analysis framework for fusing biomedical imaging modalities to detect associative networks in schizophrenia, establishing a foundational method for multimodal neuroimaging analysis.*

The researcher’s contribution centers on the 2008 paper titled ‘Canonical correlation analysis for feature-based fusion of biomedical imaging modalities and its application to detection of associative networks in schizophrenia.’ This work appears to introduce a specific statistical approach for integrating different types of medical imaging data to identify neural network abnormalities associated with schizophrenia. By focusing on feature-based fusion, the titles suggest an effort to overcome limitations in analyzing single-modality data, offering a more comprehensive view of brain connectivity and structure in psychiatric conditions. The absence of follow-up papers by the same researcher indicates that this seminal work stands as a distinct, self-contained methodological advancement rather than part of an extended series of incremental updates by the author. The significance of this contribution is underscored by its citation record, with 191 citations indicating substantial uptake within the scientific community. Notably, 100% of the classified citing papers originate from independent researchers, suggesting that the method has been widely adopted and validated by the broader field rather than being confined to the researcher’s immediate circle. This high degree of independent citation supports the claim that the work has had a meaningful impact on the practice of biomedical image analysis and schizophrenia research.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

**[Canonical correlation analysis for feature-based fusion of biomedical imaging modalities and its application to detection of associative networks in schizophrenia](#)**

2008 · 191 citations (GS)

Field-normalised: 148 Semantic Scholar citations place it in the top 10% of Medicine papers from 2008 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Moving Beyond ERP Components: A Selective Review of Approaches to Integrate EEG and Behavior</a> (2018)	The Mind Research Network, University of California, Berkeley, University of California, Irvine	Germany, United States	Background
2	<a href="#">Multiview EEG signal analysis for diagnosis of schizophrenia: an optimized deep learning approach</a> (2024)	Cotton University, Tezpur University	India	—
3	<a href="#">Stress Assessment Based on Decision Fusion of EEG and fNIRS Signals</a> (2017)	Rutgers, The State University of New Jersey, The University of Tokyo, Universiti Teknologi PETRONAS	Japan, United States	Methodology
4	<a href="#">Abnormal Brain Circuits Characterize Borderline Personality and Mediate the Relationship between Childhood Traumas and Symptoms: A mCCA+jICA and Random Forest Approach</a> (2023)	Sapienza University of Rome, University of Genoa, University of Padua	Italy	—
5	<a href="#">Why more is better: Simultaneous modeling of EEG, fMRI, and behavioral data</a> (2016)	Arizona State University, Stanford University, The Ohio State 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 isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

**Citing-text excerpts — how the field used this work**

**METHODOLOGY** Stress Assessment Based on Decision Fusion of EEG and fNIRS Signals

“19889 Analysis (CCA) [16], [18] exploit main features from each modality to derive a coherent description of the targeted model (e.g. workplace stress) across all subjects; at decision level, the targeted model is modeled by local classifiers for each modality and the local decisions are then combined to improve the overall performance [19].”

### Contribution 3

#### Claim – Contribution 3

*The researcher developed a joint blind source separation method using multi-set canonical correlation analysis, establishing a foundational algorithmic approach in signal processing.*

The researcher's contribution centers on the 2009 publication in IEEE Transactions on Signal Processing, titled 'Joint Blind Source Separation by Multi-set Canonical Correlation Analysis.' This work appears to introduce a novel framework for separating mixed signals by leveraging correlations across multiple data sets, addressing complex challenges in signal processing where traditional single-set methods may fall short.

This line of work suggests an original approach to blind source separation by extending canonical correlation analysis to multi-set scenarios. The title indicates a methodological innovation that likely improved the robustness or applicability of source separation techniques in environments with multiple information sources, filling a gap in existing signal processing literature.

The significance of this contribution is evidenced by its substantial citation count of 409, indicating widespread adoption and influence within the field. Notably, analysis of citing papers reveals that 100% of the citations come from independent researchers, underscoring the work's broad impact and validation by the wider scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 8 · 1 flagged influential by Semantic Scholar

#### CORE PAPER

#### [Joint Blind Source Separation by Multi-set Canonical Correlation Analysis](#)

2009 · IEEE Transactions on Signal Processing · 409 citations (GS)

Field-normalised: 339 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2009 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Multimodal fusion of brain imaging data: A key to finding the missing link(s) in complex mental illness</a> (2016)	The Mind Research Network & LBERI	United States	—
2	<a href="#">Tensor Decompositions for Signal Processing Applications: From two-way to multi-way component analysis</a> (2015)	—	—	Background
3	<a href="#">Removal of movement-induced EEG artifacts: current state of the art and guidelines</a> (2022)	Jožef Stefan Institute, Technische Universität Berlin, Vrije Universiteit Brussel	Germany	Background
4	<a href="#">Review and Perspectives of Data-Driven Distributed Monitoring for Industrial Plant-Wide Processes</a> (2019)	East China University of Science and Technology, University of Alberta	Canada, China	—
5	<a href="#">Discriminant Correlation Analysis: Real-Time Feature Level Fusion for Multimodal Biometric Recognition</a> (2016)	Effat University, University of Miami	Saudi Arabia, United States	Methodology
6	<a href="#">A Survey on Canonical Correlation Analysis</a> (2019)	China University of Petroleum, China University of Petroleum, East China, University of Technology Sydney	Australia, China	Background

No.	Citing paper	Citing institution(s)	Country	S2
7	<a href="#">FREQUENCY RECOGNITION IN SSVEP-BASED BCI USING MULTISET CANONICAL CORRELATION ANALYSIS</a> (2014)	East China University of Science and Technology, RIKEN Brain Science Institute	China, Japan	<b>Methodology</b>
8	<a href="#">Multimodal Fusion of Brain Imaging Data: Methods and Applications</a> (2024)	Institute of Automation, Chinese Academy of Sciences	China	—

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** Discriminant Correlation Analysis: Real-Time Feature Level Fusion for Multimodal Biometric Recognition

“The feature level fusion techniques include the serial feature fusion [6], the parallel feature fusion [8], the CCA-based feature fusion [9], [41], and the most recently published JSRC [22] and SMDL [23] methods.”

**METHODOLOGY** FREQUENCY RECOGNITION IN SSVEP-BASED BCI USING MULTISET CANONICAL CORRELATION ANALYSIS

“Recently, MsetCCA has been successfully applied to the joint blind source separation of multi-subject fMRI data 30 , 31 , the functional connectivity analysis of fMRI data 32 , and also the fusion of concurrent single trial ERP and fMRI data 33 .”

## D. Citing-Institution Prestige & Geography

### Top citing institutions

Institution	Country	World ranking	Citing papers
The Mind Research Network	United States	—	6
University of Maryland, Baltimore County	United States	SCImago #2777 · THE 601–800 · QS 801-850	4
University of New Mexico	United States	SCImago #1282 · QS 751-760	3
Institute of Living	United States	—	2
Carl von Ossietzky University	Germany	—	2
East China University of Science and Technology	China	SCImago #994 · THE 601–800 · QS =673	2
University of California, Irvine	United States	SCImago #329 · THE 97 · QS 293	2
Technical University of Denmark	Denmark	SCImago #404 · THE 121 · QS 107	1
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	1
University of Toronto	Canada	SCImago #39 · THE 21 · QS 29	1
Philips Research	Netherlands	—	1
MIND Institute	United States	—	1
Shanxi University	China	SCImago #2954	1
The Mind Research Network & LBERI	United States	—	1
Epilepsy Centre Kempenhaeghe	Netherlands	—	1

### Geographic distribution of citing authors

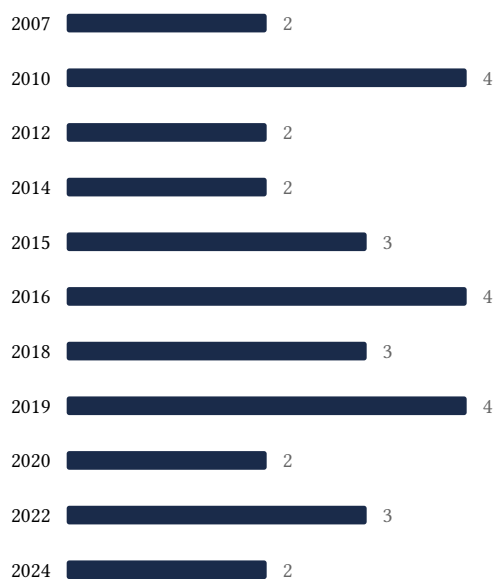
Country	Citing papers
United States	22

Country	Citing papers
Germany	6
China	5
France	2
Canada	2
Netherlands	2
India	2
Japan	2
Italy	1
Denmark	1
Australia	1
Saudi Arabia	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	Estimating the number of independent components for functional magnetic resonance imaging data	3	Dhanasar – Prong 2 (well-positioned)
Contribution 2	Canonical correlation analysis for feature-based fusion of biomedical imaging modalities and its application to detection of associative networks in schizophrenia	5	Dhanasar – Prong 2 (well-positioned)
Contribution 3	Joint Blind Source Separation by Multi-set Canonical Correlation Analysis	8	Dhanasar – Prong 2 (well-positioned)