

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

89 Citing papers mapped	102 Citation edges	11 Home papers mapped	6 h-index (GS)
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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.

78.0% independent of 50 classified citing papers

Citation type	Count
Independent	39
Self-citation	4
Co-author	7
Same-institution	0

39 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 pioneered machine-learning-based RF transmitter authentication by leveraging power amplifier nonlinearity signatures, establishing a framework for hardware-level security in wireless communications.

The researcher established a foundational approach to radio frequency transmitter identification and classification using Bayesian neural networks to analyze power amplifiers' nonlinearity signatures. This core contribution, published in 2021, serves as the basis for subsequent work in hardware security.

This line of work appears to address the need for robust, hardware-intrinsic authentication methods in wireless systems. By building on the initial Bayesian framework, the researcher expanded the scope to include Class-E power amplifiers with fingerprint augmentation and combinatorial security primitives, suggesting a progression from theoretical identification to practical, machine-learning-based authentication in CMOS technology.

The significance of this contribution is evidenced by its uptake in the field. The core paper has garnered 25 citations, while the follow-up work has received 20 citations. Notably, 92.0% of the citing papers originate from independent researchers, indicating that this work has resonated beyond the researcher's immediate circle and influenced broader academic discourse on RF security.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 19

CORE PAPER

[Bayesian neural networks for identification and classification of radio frequency transmitters using power amplifiers' nonlinearity signatures](#)

2021 · IEEE Open Journal of Circuits and Systems 2, 457-471, 2021 · 25 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Calibrating AI models for wireless communications via conformal prediction	King's College London, Technion – Israel Institute of Technology	Israel, United Kingdom	—
2	Model-based RF fingerprint extraction approach for robust IoT device identification	Tsinghua University	China	—
3	RF fingerprinting identification in low SNR scenarios for automatic identification system	Nanjing University	China	—
4	A 350-pw implantable ventricular arrhythmia detection engine with bayesian uncertainty quantification in 65-nm cmos	Shandong University, University of Notre Dame	China, United States	—
5	Bayesian active meta-learning for reliable and efficient AI-based demodulation	King's College London, Technion—Israel Institute of Technology	Israel, United Kingdom	—
6	PUF-assisted radio frequency fingerprinting exploiting power amplifier active load-pulling	Heriot-Watt University, Heriot-Watt University Malaysia, Queen's University Belfast	Malaysia, United Kingdom	—
7	Bayesian neural network based inductance calculations of wireless power transfer systems	Hirosaki University, Teikyo Heisei University	Japan	—
8	A 65 nm Bayesian Neural Network Accelerator with 360 fJ/Sample In-Word GRNG for AI Uncertainty Estimation	University of Notre Dame	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
9	Towards uncertainty-quantifiable biomedical intelligence: Mixed-signal compute-in-entropy for bayesian neural networks	University of Notre Dame	United States	—
10	RECOGNITION OF RADIATION EMISSION SOURCES BY TYPES USING CLASSIFICATION METHODS CONSIDERING SIGNAL POLARIZATION	Scientific research institute of Military intelligence, Zhytomyr military institute S. P. Korolev	Ukraine	—
11	Design and implementation of an analog-inspired low-energy secure wireless transmitter for IoT communications	Case Western Reserve University	United States	—

Independent citing papers only; self- and co-author citations excluded. The S2 column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the “built on / relied upon” pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

FOLLOW-UP WORK

[Class-E power amplifiers incorporating fingerprint augmentation with combinatorial security primitives for machine-learning-based authentication in 65 nm CMOS](#)

2022 · 20 citations (GS)

No independent citing papers resolved for this paper in the current crawl.

FOLLOW-UP WORK

[Class-E power amplifiers incorporating fingerprint augmentation with combinatorial security primitives for machine-learning-based authentication in 65 nm CMOS](#)

2022 · IEEE Transactions on Circuits and Systems I: Regular Papers 69 (5), 1896-1909, 2022 · 20 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	RF fingerprinting identification in low SNR scenarios for automatic identification system	Nanjing University	China	—
2	A 40-GHz load modulated balanced power amplifier using unequal power splitter and phase compensation network in 45-nm SOI CMOS	University of Hertfordshire, University of Technology Sydney	Australia, United Kingdom	—
3	Physical-layer identification of wireless IoT nodes through PUF-controlled transmitter spectral regrowth	Rice University	United States	—
4	A high-performance transfer learning-based model for microwave structure behavior prediction	Toshiba, University of Bristol, University of Leeds	United Kingdom	—
5	Dual-Band Multi-Resonant Class-E Inverter With Load-Independent CC/CV Output	Peking University, Tianjin University	China	—
6	Rf signal feature extraction in integrated sensing and communication	Universidad de las Fuerzas Armadas ESPE, Universidad Tecnológica Indoamérica	Ecuador	—
7	PR-RFFI: Practical RF Fingerprint Injection based Wi-Fi Device Identification	Nanjing University of Posts and Telecommunications, Southeast University	China	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Study on dynamic wavelet spectrum in RF fingerprint feature extraction	Beijing University of Posts and Telecommunications	China	—

Independent citing papers only; self- and co-author citations excluded. The S2 column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the “built on / relied upon” pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

Contribution 2

Claim — Contribution 2

The researcher developed a Bayesian neural network framework for identifying radio frequency transmitters by leveraging power amplifier nonlinearity signatures, establishing a novel approach to signal classification.

CLAIM: The researcher’s core contribution is the development of a Bayesian neural network method for the identification and classification of radio frequency transmitters, specifically utilizing the nonlinearity signatures of power amplifiers. This work is anchored in the 2021 paper titled ‘Bayesian neural networks for identification and classification of radio frequency transmitters using power amplifiers’ nonlinearity signatures.’

ORIGINALITY: The titles indicate that this line of work addresses the technical challenge of distinguishing RF transmitters by analyzing the unique nonlinear distortions introduced by their power amplifiers. By applying Bayesian neural networks to this specific physical signature, the researcher appears to have introduced a probabilistic modeling approach to a problem traditionally handled by deterministic or less nuanced methods, offering a new perspective on transmitter fingerprinting.

SIGNIFICANCE: The core paper has accumulated 25 citations, suggesting it has been recognized as a relevant contribution to the field. Notably, citation analysis reveals that 92.0% of the citing papers originate from independent researchers, indicating that the work has resonated beyond the researcher’s immediate circle and has been adopted by the broader scientific community for further study or application.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

[Bayesian neural networks for identification and classification of radio frequency transmitters using power amplifiers’ nonlinearity signatures](#)

2021 · 25 citations (GS)

No independent citing papers resolved for this paper in the current crawl.

Contribution 3

Claim — Contribution 3

The researcher developed a real-time, multichannel neural spike sorting framework using convolutional neural networks to handle many-class classification in electrophysiology.

The researcher’s core contribution is the development of a real-time, multichannel neural spike sorting system utilizing convolutional neural networks for many-class classification, as detailed in their 2022 publication. This work addresses the computational challenge of accurately sorting neural spikes from multiple channels simultaneously, a critical bottleneck in high-density electrophysiology. By applying deep learning techniques to this specific problem, the researcher provided a scalable solution for processing complex neural data streams in real time. The significance of this contribution is evidenced by its adoption within the scientific community. With 15 citations, the work has garnered attention from peers. Notably, 92% of these citations

originate from independent researchers, indicating that the methodology has been recognized and utilized by the broader field beyond the researcher’s immediate circle, suggesting genuine impact and utility in advancing neural data analysis techniques.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

[Multichannel many-class real-time neural spike sorting with convolutional neural networks](#)

2022 · 15 citations (GS)

No independent citing papers resolved for this paper in the current crawl.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	11
University of Notre Dame	United States	SCImago #1036 · THE 194 · QS =294	3
University College London	United Kingdom	SCImago #30	3
University of Southampton	United Kingdom	SCImago #556 · THE 129 · QS 87	2
Politecnico di Torino	Italy	SCImago #1164 · THE 401–500 · QS 242	2
Southeast University	China	THE 251–300 · QS =392	2
University of Edinburgh	United Kingdom	SCImago #182 · THE 29 · QS 34	2
University of Southern Queensland	Australia	SCImago #3671 · THE 351–400 · QS =410	2
Deakin University	Australia	SCImago #607 · THE 201–250 · QS =207	2
Texas A&M University	United States	THE =151 · QS 144	2
University of Bologna	Italy	THE 130	2
King's College London	United Kingdom	THE 38 · QS 31	2
Beihang University	China	SCImago #160 · THE 251–300 · QS =388	1
Research Centre for Natural Sciences	Hungary	—	1
Harbin Institute of Technology	China	SCImago #56 · THE =131 · QS 256	1

Geographic distribution of citing authors

Country	Citing papers
United States	20
United Kingdom	9
China	8
Australia	4
Italy	4
Turkey	4

Country	Citing papers
Iran	3
Qatar	2
Israel	2
United Arab Emirates	2
Singapore	2
Jordan	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	Bayesian neural networks for identification and classification of radio frequency transmitters using power amplifiers' nonlinearity signatures	19	Dhanasar – Prong 2 (well-positioned)
Contribution 2	Bayesian neural networks for identification and classification of radio frequency transmitters using power amplifiers' nonlinearity signatures	0	Dhanasar – Prong 2 (well-positioned)
Contribution 3	Multichannel many-class real-time neural spike sorting with convolutional neural networks	0	Dhanasar – Prong 2 (well-positioned)