

# Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

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

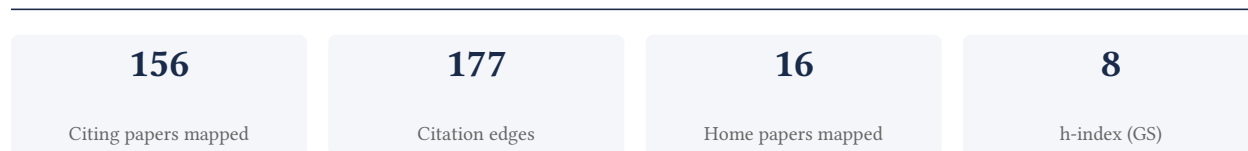
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[Google Scholar profile](#)

**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



### 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.

**80.8% independent** of 52 classified citing papers

Citation type	Count
Independent	42
Self-citation	9
Co-author	1
Same-institution	0

104 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 data-efficient GAN training via architectural reconfiguration, establishing a foundational framework subsequently extended to medical imaging alignment and dynamic pruning techniques.*

The researcher's core contribution centers on the 2023 paper 'Re-GAN: Data-Efficient GANs Training via Architectural Reconfiguration,' which proposes a novel approach to training generative adversarial networks with limited data. This work serves as the foundation for a sustained line of inquiry into efficient generative modeling.

This line of work appears to address the computational and data-intensive challenges inherent in standard GAN training. By focusing on architectural reconfiguration, the researcher introduced a method to optimize training efficiency. The subsequent 2024 paper, 'RG-GAN: Dynamic Regenerative Pruning for Data-Efficient Generative Adversarial Networks,' suggests an evolution of this concept, applying dynamic pruning techniques to further enhance efficiency. The 2025 follow-up, 'Data-Efficient Alignment in Medical Imaging via Reconfigurable Generative Networks,' indicates the application of these reconfigurable principles to the specific domain of medical imaging alignment, demonstrating the versatility of the initial framework.

The significance of this contribution is evidenced by its adoption within the research community. The core paper has accumulated 34 citations, while the 2024 follow-up has garnered 16 citations, indicating sustained interest in these efficiency methods. Notably, among 52 classified citing papers, 42 (80.8%) originate from independent researchers, suggesting that this work has influenced scholars outside the researcher's immediate institution and collaboration network, thereby validating its broader impact on the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 13 · 2 flagged influential by Semantic Scholar

### CORE PAPER

#### [Re-GAN: Data-Efficient GANs Training via Architectural Reconfiguration](#)

2023 · CVPR 2023 and IEEE TPAMI 2025, 2023 · 34 citations (GS)

Field-normalised: 23 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2023 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Generative Artificial Intelligence Meets Synthetic Aperture Radar: A Survey</a>	Fudan University, German Aerospace Center, Northwestern Polytechnical University	China, Germany	—
2	<a href="#">Image synthesis under limited data: A survey and taxonomy</a>	East China University of Science and Technology	China	Influential
3	<a href="#">A survey on generative modeling with limited data, few shots, and zero shot</a>	Singapore University of Technology and Design, Singapore University of Technology and Design, Stanford University	Singapore	Methodology
4	<a href="#">Generative adversarial networks with learnable auxiliary module for image synthesis</a>	Chinese Academy of Agricultural Sciences, Chongqing University, Southwest University	China	—
5	<a href="#">Cycleganas: Differentiable neural architecture search for cyclegan</a>	Korea University	South Korea	Background
6	<a href="#">Generative AI for interdisciplinary collaborative design: an agent-based workflow or-</a>	Tianjin University, Tianjin University of Science and	China, South Africa	—

No.	Citing paper	Citing institution(s)	Country	S2
	<a href="#">chestration framework guided by R<sup>3</sup> invariants</a>	Technology, University of South Africa		
7	<a href="#">Improving few-shot image generation by structural discrimination and textural modulation</a>	East China University of Science and Technology	China	Background
8	<a href="#">Research on maritime target ship generation using improved deep convolutional generative adversarial network</a>	Yantai University	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** A survey on generative modeling with limited data, few shots, and zero shot

“Methods: *CbC*[155], *DynamicD*[191], *AdvAug*[21], *Re-GAN*[151], *AutoInfoGAN* [157]”

### FOLLOW-UP WORK

#### [Data-Efficient Alignment in Medical Imaging via Reconfigurable Generative Networks](#)

2025 · WACV 2025, 2025 · 1 citations (GS)

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

### FOLLOW-UP WORK

#### [RG-GAN: Dynamic Regenerative Pruning for Data-Efficient Generative Adversarial Networks](#)

2024 · AAAI 2024, 2024 · 16 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Image synthesis under limited data: A survey and taxonomy</a>	East China University of Science and Technology	China	—
2	<a href="#">Generative AI through CAS lens: An integrated overview of algorithmic optimizations, architectural advances, and automated designs</a>	—	—	—
3	<a href="#">IDAP++: Advancing Divergence-Aware Pruning with Joint Filter and Layer Optimization</a>	Way LLC	Russia, United States	—
4	<a href="#">Inference Acceleration of Autoregressive Normalizing Flows by Selective Jacobi Decoding</a>	Purdue University, Rice University	United States	—
5	<a href="#">IDAP++: Advancing Divergence-Based Pruning via Filter-Level and Layer-Level Optimization</a>	Way LLC	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 direction alignment inspection method to detect backdoor attacks in federated learning, subsequently extending this framework to include traceable black-box watermarks for model provenance.*

The researcher’s core contribution centers on the 2025 paper ‘Detecting Backdoor Attacks in Federated Learning via Direction Alignment Inspection,’ which established a novel approach for identifying malicious updates within distributed training environments. This work serves as the foundation for a broader security framework in federated systems.

This line of work appears to address the critical vulnerability of backdoor attacks in collaborative machine learning, where individual participants may inject malicious patterns. The subsequent 2026 paper, ‘Traceable Black-box Watermarks for Federated Learning,’ suggests an expansion of this research to include mechanisms for verifying model integrity and origin, indicating a comprehensive strategy for securing federated learning pipelines.

The significance of this contribution is evidenced by 27 citations for the core paper and 2 for the follow-up. Notably, 80.8% of the 52 classified citations originate from independent researchers, demonstrating that the academic community widely recognizes and builds upon these methods for enhancing federated learning security.

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

#### CORE PAPER

### [Detecting Backdoor Attacks in Federated Learning via Direction Alignment Inspection](#)

2025 · CVPR 2025 (Highlight), 2025 · 27 citations (GS)

Field-normalised: 14 Semantic Scholar citations place it in the top 10% of Computer Science papers from 2025 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Sok: The last line of defense: On backdoor defense evaluation</a>	Delft University of Technology, Ikerlan Research Center, Radboud University	Italy, Netherlands, Norway	—
2	<a href="#">Poison Once, Refuse Forever: Weaponizing Alignment for Injecting Bias in LLMs</a>	Queen's University Belfast, University of California, Riverside	United Kingdom, United States	—
3	<a href="#">Dynamic Min-Max Multi-Dimensional Reinforcement Backdoor Attacks and Orchestrated Closed-Loop Defense in Fairness-Aware Web Federated Finance</a>	Donghua University, Tongji University	China	—
4	<a href="#">BackFed: An Efficient &amp; Standardized Benchmark Suite for Backdoor Attacks in Federated Learning</a>	Vanderbilt University, VinUniversity	United States, Vietnam	—
5	<a href="#">Defending the Edge: Representative-Attention Defense against Backdoor Attacks in Federated Learning</a>	University of Manchester, University of Manchester & MBZUAI	United Arab Emirates, United Kingdom	—
6	<a href="#">Early detection of backdoor attacks in federated learning via ecosystemic symmetry breaking</a>	Universidad de Castilla La Mancha	Spain	—
7	<a href="#">Stealth by Conformity: Evading Robust Aggregation through Adaptive Poisoning</a>	Queen’s University Belfast	United Kingdom	—

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).

#### FOLLOW-UP WORK

### [Traceable Black-box Watermarks for Federated Learning](#)

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">EmbTracker: Traceable Black-box Water-marking for Federated Language Models</a>	Ant Group, Shanghai Jiao-tong University, Shanghai Jiao Tong University	China, Hong Kong	Influential

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 established a foundational survey framework for federated learning in smart grids, systematically mapping applications and identifying critical security vulnerabilities.*

The researcher’s contribution centers on the 2024 paper 'Federated Learning for Smart Grid: A Survey on Applications and Potential Vulnerabilities.' This work serves as the core reference point for this line of inquiry, synthesizing existing knowledge to define the landscape of privacy-preserving machine learning within energy infrastructure.

This line of work appears to address the emerging need to understand how federated learning can be securely deployed in smart grid environments. By focusing on both applications and potential vulnerabilities, the researcher provided a structured overview that likely helped clarify the intersection of distributed AI and critical infrastructure security, a topic that requires careful balancing of efficiency and risk.

The significance of this contribution is evidenced by its rapid uptake, with 59 citations recorded. Notably, 80.8% of the citing papers originate from independent researchers, suggesting that the work has resonated broadly across the academic community beyond the researcher’s immediate circle. This high degree of independent citation indicates that the survey has become a recognized reference point for scholars exploring secure federated learning in energy systems.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

#### CORE PAPER

#### [Federated Learning for Smart Grid: A Survey on Applications and Potential Vulnerabilities](#)

2024 · ACM TCPS 2025, 2024 · 59 citations (GS)

Field-normalised: 30 Semantic Scholar citations place it in the top 5% of Engineering papers from 2024 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">A comprehensive review of AI agents: Transforming possibilities in technology and beyond</a>	Brown University, George Washington University, Independent Researcher	United States	—
2	<a href="#">Clustered federated learning for generalizable fdia detection in smart grids with heterogeneous data</a>	Shenzhen University, The University of Hong Kong, University of California, Santa Barbara	China, Hong Kong, United States	—
3	<a href="#">Federated learning for enhancing extrapolation ability of HVAC models: case study on two real-life DOAS units</a>	Seoul National University	South Korea	—

No.	Citing paper	Citing institution(s)	Country	S2
4	<a href="#">A Collaborative Adaptive Cybersecurity Algorithm for Cognitive Cities</a>	George Washington University, Gulf University for Science and Technology	Kuwait, United States	—
5	<a href="#">Federated Spatiotemporal Graph Learning for Passive Attack Detection in Smart Grids</a>	American University of Beirut	Lebanon	—

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
University of Nevada, Reno	United States	SCImago #2284 · QS 1001-1200	9
Oak Ridge National Laboratory	United States	SCImago #915	4
The Hong Kong Polytechnic University	Hong Kong	SCImago #256 · THE 80 · QS 54	3
Zhejiang University	China	SCImago #6 · THE 39 · QS 49	2
Chongqing University	China	SCImago #167 · THE 351-400 · QS =504	2
East China University of Science and Technology	China	SCImago #994 · THE 601-800 · QS =673	2
The University of Hong Kong	Hong Kong	SCImago #195 · THE 33 · QS 11	2
Singapore University of Technology and Design	Singapore	SCImago #977 · QS =519	2
Wayy LLC	United States	—	2
Purdue University	United States	SCImago #255 · QS =88	2
The Hong Kong University of Science and Technology (Guangzhou)	China	SCImago #483 · THE =58 · QS 44	2
George Washington University	United States	SCImago #832 · THE 201-250 · QS =358	2
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	2
Tongji University	China	SCImago #82 · THE =141 · QS =177	1
University of South Africa	South Africa	SCImago #2768 · THE 1201-1500 · QS 901-950	1

### Geographic distribution of citing authors

Country	Citing papers
United States	26
China	18
United Kingdom	5
Hong Kong	3

Country	Citing papers
Singapore	2
Australia	2
South Korea	2
Spain	2
United Arab Emirates	2
South Africa	1
Turkey	1
Vietnam	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.

## F. AAO Precedent Considerations

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### 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

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Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

<b>Contribution</b>	<b>Core paper</b>	<b>Indep. cites</b>	<b>Supports</b>
Contribution 1	Re-GAN: Data-Efficient GANs Training via Architectural Reconfiguration	13	8 CFR 204.5(i)(3) – Outstanding Researcher
Contribution 2	Detecting Backdoor Attacks in Federated Learning via Direction Alignment Inspection	8	8 CFR 204.5(i)(3) – Outstanding Researcher
Contribution 3	Federated Learning for Smart Grid: A Survey on Applications and Potential Vulnerabilities	5	8 CFR 204.5(i)(3) – Outstanding Researcher