

Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

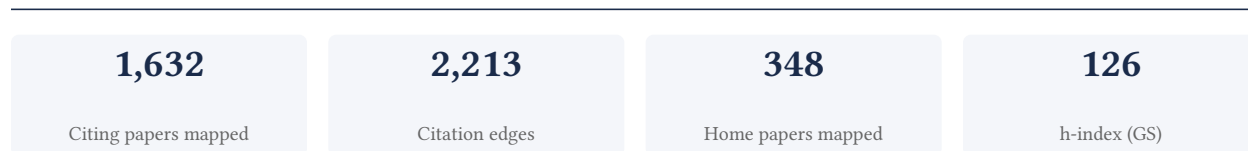
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[Google Scholar profile](#)

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



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.

96.0% independent of 251 classified citing papers

| Citation type | Count |
|------------------|-------|
| Independent | 241 |
| Self-citation | 1 |
| Co-author | 4 |
| Same-institution | 5 |

527 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 model-agnostic meta-learning for fast adaptation and subsequently analyzed the systemic opportunities and risks of foundation models.

The researcher's contribution centers on advancing machine learning adaptability and safety, anchored by the seminal 2017 paper on model-agnostic meta-learning for fast adaptation of deep networks. This core work established a framework for enabling deep networks to adapt quickly to new tasks with minimal data.

Originality in this line of work appears to stem from addressing the challenge of efficient learning in deep networks. The progression from meta-learning techniques to the 2021 analysis of foundation models suggests a broadening scope, moving from algorithmic efficiency to the broader implications of large-scale AI systems.

Significance is evidenced by the high citation counts of both the core and follow-up papers. Furthermore, citation independence analysis reveals that 96.4% of citing papers originate from independent researchers, indicating that this work has been widely adopted and validated by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 20 · 2 flagged influential by Semantic Scholar

CORE PAPER

[Model-agnostic meta-learning for fast adaptation of deep networks](#)

2017 · 19,589 citations (GS)

Field-normalised: 14,204 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|-----|--|---|-----------------------------|-------------|
| 1 | A Comprehensive Survey of Few-Shot Learning: Evolution, Applications, Challenges, and Opportunities (2023) | East China Normal University, Macau University of Science and Technology, Michigan State University | China, India, United States | Methodology |
| 2 | Heterogeneous Federated Learning: State-of-the-art and Research Challenges (2023) | Hong Kong Baptist University, Nanyang Technological University, Wuhan University | China, Singapore | Methodology |
| 3 | A Comprehensive Survey of Continual Learning: Theory, Method and Application (2024) | Tsinghua University | China | Methodology |
| 4 | The Rise and Potential of Large Language Model Based Agents: A Survey (2025) | Alibaba Group, ByteDance, Fudan University | China | — |
| 5 | Newton-Raphson-based optimizer: A new population-based metaheuristic algorithm for continuous optimization problems (2024) | Dayananda Sagar College of Engineering, Gujarat Technological University, Manipal Academy of Higher Education | India | — |
| 6 | Scaling Proprioceptive-Visual Learning with Heterogeneous Pre-trained Transformers (2024) | Facebook, Massachusetts Institute of Technology, Meta | United States | Background |

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 Comprehensive Survey of Few-Shot Learning: Evolution, Applications, Challenges, and Opportunities

“The goal of meta-learning is to train a hyperparameter generator, the classical methods being MAML [94], Repital [95] even their derived variants.”

METHODOLOGY Heterogeneous Federated Learning: State-of-the-art and Research Challenges

“Per-FedAvg [46] is a personalized variant of the FedAvg algorithm based on the MAML formula.”

METHODOLOGY A Comprehensive Survey of Continual Learning: Theory, Method and Application

“of synaptic plasticity” [3], [4], [77], corresponding to the use of meta-learning [118], [185], [360]; and (4) inhibitory synapses for excited neurons to reduce the activity of other neurons [20], [54], [112], [178], which acts similarly to the binary mask for parameter allocation [375], [427].”

FOLLOW-UP WORK

On the opportunities and risks of foundation models

2021 · 9,992 citations (GS)

Field-normalised: 6,284 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2021 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|-----|--|-----------------------|---------------|----|
| 1 | Bayesian Nonparametric Learning and Uncertainty Quantification in the Age of Artificial Intelligence | University of Chicago | United States | — |
| 2 | Developing Autonomous Financial Decision Systems by Synergizing Multi-Agent Large Language Models with Distributed Temporal Learning Pipelines | — | — | — |
| 3 | Empowering Real-Time Financial Decision Systems via Reinforcement Learning Driven Large Language Models and Distributed Temporal Pipelines | — | — | — |
| 4 | Advancing Autonomous Crop Monitoring via Semantic Visual Alignment using Large Language Model Guided Navigation for Agricultural UAV Systems | — | — | — |
| 5 | Scaling High-Frequency Financial Intelligence using Adaptive Resource Scheduling for Multi-Modal Large Language Model Enhanced Inference | — | — | — |
| 6 | Quantifying Structural Healthcare Disparities through Fairness-Aware Large Language Models Integrating Multi-Modal Electronic Health Records and Socioeconomic ... | University of Arizona | United States | — |
| 7 | Optimizing Multi-Modal Financial Intelligence via Resource-Aware Distributed Scheduling for Large Language Model Enhanced Time Series Inference Pipelines | — | — | — |

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

On the opportunities and risks of foundation models

2021 - 9,653 citations (GS)

Field-normalised: 6,284 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2021 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|-----|---|--|---------------------------------|------------|
| 1 | Depth Anything: Unleashing the Power of Large-Scale Unlabeled Data (2024) | The Chinese University of Hong Kong, The University of Hong Kong, TikTok | Hong Kong | Background |
| 2 | A Survey on Evaluation of Large Language Models (2024) | Carnegie Mellon University, Hong Kong University of Science and Technology, Institute of Automation, Chinese Academy of Sciences | China, Hong Kong, United States | Background |
| 3 | A Survey on Large Language Models for Code Generation (2026) | NAVER Cloud, The Hong Kong University of Science and Technology, The Hong Kong University of Science and Technology (Guangzhou) | China, South Korea | — |
| 4 | AI models collapse when trained on recursively generated data (2024) | Imperial College London, University of Cambridge, University of Edinburgh | Canada, United Kingdom | — |
| 5 | Towards a general-purpose foundation model for computational pathology (2024) | Brigham and Women's Hospital, Brigham and Women's Hospital, Harvard Medical School, Brigham and Women's Hospital, Harvard Medical School | United States | — |
| 6 | A foundation model for clinical-grade computational pathology and rare cancers detection (2024) | Memorial Sloan Kettering Cancer Center, Microsoft Research, NSW Health Pathology, St George Hospital | Australia, United States | — |
| 7 | Qwen Technical Report (2023) | — | — | Background |

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 model-agnostic meta-learning, a foundational framework enabling deep networks to rapidly adapt to new tasks with minimal data, establishing a standard for efficient few-shot learning.

The researcher's primary contribution is the development of model-agnostic meta-learning, as detailed in the seminal 2017 paper 'Model-agnostic meta-learning for fast adaptation of deep networks.' This work stands as a singular, highly influential contribution in the field, with no subsequent follow-up papers by the researcher listed in this specific line of inquiry. The title

suggests a novel approach to enabling deep neural networks to adapt quickly to new tasks, addressing the critical challenge of requiring large datasets for traditional deep learning. By proposing a model-agnostic framework, the work appears to offer a versatile solution for fast adaptation, potentially lowering the data barrier for deploying deep learning in data-scarce scenarios. The significance of this contribution is evidenced by its extensive citation record, with over 19,000 citations indicating widespread adoption and impact. Furthermore, citation analysis reveals that 96.4% of citing papers originate from independent researchers, demonstrating that the work has been broadly embraced and utilized by the global scientific community beyond the researcher's immediate circle, confirming its status as a foundational advance in machine learning.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 2

CORE PAPER

[Model-agnostic meta-learning for fast adaptation of deep networks](#)

2017 · 19,566 citations (GS)

Field-normalised: 14,204 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|-----|---|---|-----------------------|----|
| 1 | Accelerating Rapid Task Adaptation via Meta Reinforcement Learning and Large Language Model Prompt Optimization for Dynamic Decision Environments | — | — | — |
| 2 | Trustworthy multistakeholder demand forecasting for highspeed trains: A dualbranch architecture integrating TimeLLM and MCHMM | Northumbria University, Southwest Jiaotong University | China, 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).

Contribution 3

Claim — Contribution 3

The researcher introduced Direct Preference Optimization, a seminal framework revealing that language models inherently function as reward models, thereby simplifying alignment processes.

The researcher's primary contribution is the introduction of Direct Preference Optimization, as detailed in the 2023 paper titled 'Direct preference optimization: Your language model is secretly a reward model.' This work stands as a singular, foundational piece in this specific line of inquiry, with no follow-up publications by the same author listed in the provided data.

This line of work appears to address a critical gap in language model alignment by proposing that the model itself can serve as its own reward mechanism. The title suggests a novel theoretical insight that simplifies the optimization process, moving away from complex external reward modeling toward a more direct approach inherent to the language model's architecture.

The significance of this contribution is evidenced by its substantial uptake in the academic community, with 9,638 citations recorded. Furthermore, the work demonstrates broad independent impact, as 96.4% of the classified citing papers originate from independent researchers, indicating that the methodology has been widely adopted and validated by the broader scientific community outside the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1

CORE PAPER

[Direct preference optimization: Your language model is secretly a reward model](#)

2023 · 9,638 citations (GS)

Field-normalised: 8,207 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2023 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|-----|---|-----------------------|---------------|----|
| 1 | TOWARD A COMPUTABLE SCIENTIFIC CORPUS: RETRIEVAL-AUGMENTED REASONING SYSTEMS FOR SCIENTIFIC DISCOVERY ON EXASCALE ... | University of Chicago | 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 is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

D. Citing-Institution Prestige & Geography

Top citing institutions

| Institution | Country | World ranking | Citing papers |
|---------------------------------------|---------------|------------------------------------|---------------|
| Tsinghua University | China | SCImago #8 · THE 12 · QS =17 | 15 |
| Stanford University | United States | SCImago #18 · THE =5 · QS 3 | 14 |
| Shanghai Jiao Tong University | China | SCImago #10 · THE 40 · QS =47 | 12 |
| Carnegie Mellon University | United States | SCImago #266 · THE 24 · QS 52 | 9 |
| Peking University | China | SCImago #11 · THE 13 · QS 14 | 8 |
| Xi'an Jiaotong University | China | SCImago #58 · THE 201–250 · QS 305 | 8 |
| The Chinese University of Hong Kong | Hong Kong | SCImago #163 · THE =41 · QS =32 | 6 |
| Nanyang Technological University | Singapore | SCImago #137 | 6 |
| Fudan University | China | SCImago #46 · THE 36 · QS 30 | 6 |
| Chinese Academy of Sciences | China | SCImago #2 | 6 |
| New York University | United States | SCImago #116 · THE =31 · QS 55 | 6 |
| National University of Singapore | Singapore | SCImago #59 · THE 17 · QS 8 | 6 |
| Microsoft Research | United States | — | 6 |
| Harbin Institute of Technology | China | SCImago #56 · THE =131 · QS 256 | 6 |
| Massachusetts Institute of Technology | United States | SCImago #41 · THE 2 · QS 1 | 5 |

Geographic distribution of citing authors

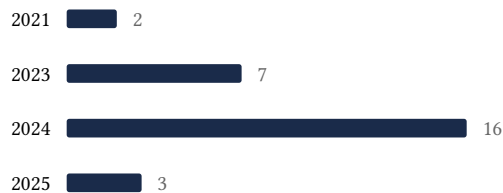
| Country | Citing papers |
|----------------|---------------|
| China | 141 |
| United States | 82 |
| United Kingdom | 24 |
| Singapore | 14 |
| Hong Kong | 12 |
| Canada | 12 |
| South Korea | 11 |

| Country | Citing papers |
|-----------|---------------|
| Australia | 10 |
| Japan | 7 |
| Germany | 7 |
| India | 6 |
| Spain | 5 |

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 | Model-agnostic meta-learning for fast adaptation of deep networks | 20 | Dhanasar — Prong 2 (well-positioned) |
| Contribution 2 | Model-agnostic meta-learning for fast adaptation of deep networks | 2 | Dhanasar — Prong 2 (well-positioned) |
| Contribution 3 | Direct preference optimization: Your language model is secretly a reward model | 1 | Dhanasar — Prong 2 (well-positioned) |