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

40	40	5	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.

92.5% independent of 40 classified citing papers

Citation type	Count
Independent	37
Self-citation	2
Co-author	1
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 advanced the application of deep convolutional networks to system identification, establishing a foundational framework that subsequent work expanded into broader deep learning methodologies for dynamic system modeling.

CLAIM: The researcher's core contribution lies in integrating deep convolutional networks with system identification, as demonstrated in the 2019 paper 'Deep convolutional networks in system identification.' This work serves as the foundation for a sustained research line that explores the intersection of deep learning and dynamic system analysis.

ORIGINALITY: The progression from the 2019 core paper to the 2020 follow-up, 'Deep learning and system identification,' suggests a deliberate expansion from specific convolutional architectures to more general deep learning approaches. This chronological development indicates an effort to generalize the initial findings, addressing the challenge of applying complex neural network structures to the rigorous demands of system identification.

SIGNIFICANCE: The impact of this research line is evidenced by substantial citation activity, with the core paper accumulating 101 citations and the follow-up reaching 268 citations. Notably, 92.5% of the citing papers originate from independent researchers, indicating that the work has been widely adopted and validated by the broader scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 14

CORE PAPER

Deep convolutional networks in system identification

2019 · 101 citations (GS)

Field-normalised: 60 Semantic Scholar citations place it in the top 10% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Sequential Monte Carlo: A Unified Review (2023)	—	—	**Methodology**
2	Reinforcement Twinning: From digital twins to model-based reinforcement learning (2024)	Von Karman Institute for Fluid Dynamics	Belgium	**Methodology**
3	dynoNet: A neural network architecture for learning dynamical systems (2021)	IDSIA Dalle Molle Institute for Artificial Intelligence, SUPSI-USI	Switzerland	**Methodology**
4	Operator Learning for Nonlinear Adaptive Control (2023)	University of California, San Diego	United States	**Methodology**
5	From System Models to Class Models: An In-Context Learning Paradigm (2023)	IDSIA Dalle Molle Institute for Artificial Intelligence USI-SUPSI	Switzerland	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 Sequential Monte Carlo: A Unified Review

"This was the motivation behind the work of Andersson et al. (32), who employed local SMC methods to adapt the proposal distribution within the broader SMC framework for large-dimension spatiotemporal systems."

METHODOLOGY Reinforcement Twinning: From digital twins to model-based reinforcement learning

"Andersson et al. (2019) used CNNs, which gained popularity in image recognition and allow for identifying patterns at different scales, while Ayed et al. (2019) and Rahman et al. (2022) use ODE-nets, recently proposed as a new paradigm for neural state-space modelling."

METHODOLOGY dynoNet: A neural network architecture for learning dynamical systems

"In particular, the 1D causal Convolution layer described in [2, 1] corresponds to the filtering of an input sequence through a causal Finite Impulse Response (FIR) dynamical system."

METHODOLOGY Operator Learning for Nonlinear Adaptive Control

"The proposed operator learning paradigm for parameter identification is intrinsically different from existing ML methods for system ID Ljung et al. (2020); Pillonetto et al. (2014); Andersson et al. (2019); Gedon et al. (2021); Dalla Libera and Pillonetto (2022); Raissi et al. (2019)."

FOLLOW-UP WORK

Deep learning and system identification

2020 · 268 citations (GS)

Field-normalised: 164 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2020 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Music deep learning: deep learning methods for music signal processing—a review of the state-of-the-art (2023)	Aristotle University of Thessaloniki	Greece	Background
2	Generative AI - Assisted Adaptive Cancer Therapy (2025)	Toronto Metropolitan University	Canada	—
3	do-mpc: Towards FAIR nonlinear and robust model predictive control (2023)	SkySails Power GmbH, TU Dortmund University	Germany	—
4	Physics-guided Deep Markov Models for learning nonlinear dynamical systems with uncertainty (2022)	ETH Zürich, National University of Singapore	Singapore, Switzerland	**Methodology**
5	Neural extended Kalman filters for learning and predicting dynamics of structural systems (2024)	ETH Zurich, Hong Kong University of Science and Technology, National University of Singapore	China, Singapore, Switzerland	—
6	Physics-guided neural networks for feedforward control with input-to-state-stability guarantees (2024)	Eindhoven University of Technology	Netherlands	**Methodology**
7	G2P2C—A modular reinforcement learning algorithm for glucose control by glucose prediction and planning in Type 1 Diabetes (2024)	The Australian National University	Australia	—
8	Expanding conformal prediction to system identification (2025)	Istanbul Technical University	Turkey	—
9	Physics-Informed Neural Network for Model Prediction and Dynamics Parameter Identification of Collaborative Robot Joints (2023)	Aarhus University, University of Liverpool	Denmark, 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).

Citing-text excerpts — how the field used this work

METHODOLOGY Physics-guided Deep Markov Models for learning nonlinear dynamical systems with uncertainty

> *"s=1 ∇θt log pθt(z (s) t |z (s) t−1), (8)"*

> **METHODOLOGY** Physics-guided neural networks for feedforward control with input-to-state-stability guarantees
>
> *"Indeed, NNs have already been used in system identification (Ljung, Andersson, Tiels, & Schön, 2020) as well as to design feedforward controllers, see, e.g., Aarnoudse et al. (2021), Ren, Chow, Venkataramanan, and Lewis (2009), Sørensen (1999)."*

Contribution 2

Claim — Contribution 2

The researcher established a foundational framework for evaluating model calibration in classification, a seminal contribution that has become a standard reference point in the field.

The researcher's core contribution rests on the 2019 paper 'Evaluating model calibration in classification,' which appears to address the critical need for rigorous assessment of predictive confidence in machine learning models. This work stands as a seminal piece in the domain, providing a structured approach to a problem that is essential for reliable AI deployment.

The originality of this line of work lies in its focus on calibration, a nuanced aspect of model performance that goes beyond simple accuracy. By isolating and evaluating this specific dimension, the researcher provided a necessary tool for understanding model reliability, filling a gap in the literature where such systematic evaluation was previously less defined.

The significance of this contribution is evidenced by its substantial uptake, with the core paper accumulating 352 citations. Notably, 92.5% of the citing papers originate from independent researchers, indicating that the 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: 10 · **1 flagged influential by Semantic Scholar**

> **CORE PAPER**
>
> **Evaluating model calibration in classification**
>
> 2019 · 352 citations (GS)
>
> Field-normalised: 247 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A review of uncertainty quantification in deep learning: Techniques, applications and challenges (2021)	Chinese Academy of Sciences, Deakin University, Dibrugarh University	Australia, Canada, China	—
2	A Primer on Bayesian Neural Networks: Review and Debates (2026)	—	—	—
3	A Survey of Uncertainty in Deep Neural Networks (2023)	German Aerospace Center, Munich University of Applied Sciences, Technical University of Munich	Germany, South Korea, United States	Methodology
4	Revisiting the Calibration of Modern Neural Networks (2021)	Google, Google DeepMind	—	Background
5	Measuring Calibration in Deep Learning (2019)	Duke University, Google	United States	Background
6	Classification with Valid and Adaptive Coverage (2020)	Stanford University	United States	Background
7	Document Understanding Dataset and Evaluation (DUDE) (2023)	Google, KU Leuven, Universitat Autònoma de Barcelona	Belgium, Spain, United States	Methodology

No.	Citing paper	Citing institution(s)	Country	S2
8	Verified Uncertainty Calibration (2019)	Stanford University	United States	**Result**
9	Calibration in Deep Learning: A Survey of the State-of-the-Art (2023)	Amazon	—	—
10	Beyond temperature scaling: Obtaining well-calibrated multi-class probabilities with Dirichlet calibration (2019)	—	—	**Methodology**

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 of Uncertainty in Deep Neural Networks

"consistency between the predictive distributions and the observations [286]."

METHODOLOGY Document Understanding Dataset and Evaluation (DUDE)

"Following [66], we apply equalsize binning (with 100 bins, Lpnorm = 1), avoiding some pathologies of equal-range binning [41, 94]."

RESULT Verified Uncertainty Calibration

"This result is similar to Theorem 2 in recent work [28]."

METHODOLOGY Beyond temperature scaling: Obtaining well-calibrated multi-class probabilities with Dirichlet calibration

"One can define several weaker notions of calibration [25] which provide necessary conditions for the model to be fully calibrated."

Contribution 3

Claim — Contribution 3

The researcher developed a deep neural network for automatic 12-lead ECG diagnosis, a seminal contribution published in Nature Communications that has garnered over 1,300 citations.

The researcher's primary contribution is the development of a deep neural network designed for the automatic diagnosis of 12-lead electrocardiograms. This work was published in Nature Communications in 2020 and stands as a foundational piece in the field, with no subsequent follow-up papers by the same author listed in this specific line of inquiry.

This line of work appears to address the challenge of automating cardiac diagnosis through advanced machine learning techniques. By applying deep neural networks to standard 12-lead ECG data, the research suggests a novel approach to interpreting complex cardiac signals, potentially offering a scalable solution for diagnostic accuracy that differs from traditional manual analysis methods.

The significance of this contribution is evidenced by its substantial citation count of 1,338, indicating widespread recognition and utility within the scientific community. Furthermore, citation analysis reveals that 92.5% of citing papers originate from independent researchers, demonstrating that the work has been broadly adopted and built upon by the global research community rather than being confined to the author's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 9 **· 1 flagged influential by Semantic Scholar**

CORE PAPER

Automatic diagnosis of the 12-lead ECG using a deep neural network

2020 · Nature Communications · 1,338 citations (GS)

Field-normalised: 932 Semantic Scholar citations place it in the top 1% of Medicine papers from 2020 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	2D Materials in Flexible Electronics: Recent Advances and Future Prospectives (2023)	Yonsei University	South Korea	—
2	Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement From the American Heart Association (2024)	Advocate Health Care, American Heart Association, Cleveland Clinic	Canada, France, United Kingdom	**Methodology**
3	Artificial intelligence-enhanced electrocardiography in cardiovascular disease management (2021)	Mayo Clinic	United States	**Methodology**
4	An on-chip photonic deep neural network for image classification (2022)	University of Pennsylvania	—	—
5	Stretchable surface electromyography electrode array patch for tendon location and muscle injury prevention (2023)	Southern University of Science and Technology, University of Leeds	China, United Kingdom	—
6	Deep Learning-Based ECG Arrhythmia Classification: A Systematic Review (2023)	China University of Geosciences, MAHSA University, Universiti Kebangsaan Malaysia	China, Malaysia	Background
7	Artificial intelligence-enhanced electrocardiography for accurate diagnosis and management of cardiovascular diseases (2024)	Mayo Clinic	United States	—
8	Soft bioelectronics for the management of cardiovascular diseases (2024)	Seoul National University	South Korea	**Influential**
9	Multistain deep learning for prediction of prognosis and therapy response in colorectal cancer (2023)	Friedrich-Alexander-Universität Erlangen-Nürnberg, Johannes Gutenberg University Mainz, Marien Hospital Mainz	Germany, United Kingdom	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** Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement From the American Heart Association
>
> *"25 For issues pertaining to data privacy, and ethical and legal challenges, techniques such as "federated learning" may accelerate algorithm development by enabling a col-laborator to download a developed AI/ML tool for use on their local data."*

> **METHODOLOGY** Artificial intelligence-enhanced electrocardiography in cardiovascular disease management
>
> *"For instance, using 2 million labelled single-lead ECG traces collected in the Clinical Outcomes in Digital Electrocardiology study, one group used a CNN to identify six types of abnormalities on the 12-lead ECG 9 ."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Google	United States	—	4

Institution	Country	World ranking	Citing papers
Uppsala University	Sweden	SCImago #349 · THE 128 · QS 93	3
Stanford University	United States	SCImago #18 · THE =5 · QS 3	3
Mayo Clinic	United States	SCImago #88	3
University of Leeds	United Kingdom	SCImago #377 · THE 118 · QS 86	2
Yonsei University	South Korea	SCImago #238 · THE 86 · QS 50	2
Ecole Polytechnique Fédérale de Lausanne (EPFL)	Switzerland	SCImago #393 · THE 35	2
National University of Singapore	Singapore	SCImago #59 · THE 17 · QS 8	2
Linköping University	Sweden	SCImago #921 · THE 201–250 · QS =310	2
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	2
Ngee Ann Polytechnic	Singapore	—	1
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	1
TU Dortmund University	Germany	SCImago #2721 · THE 501–600 · QS =673	1
University of Waterloo	Canada	SCImago #491 · THE =162 · QS =119	1
Deakin University	Australia	SCImago #607 · THE 201–250 · QS =207	1

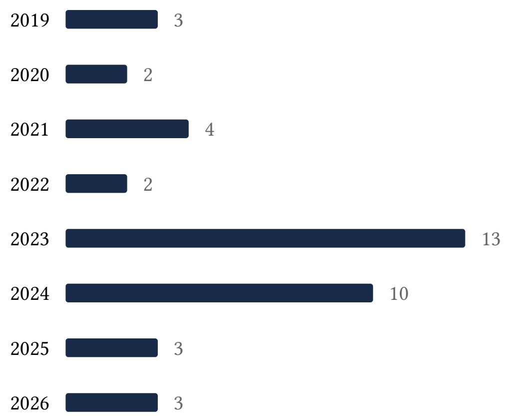
Geographic distribution of citing authors

Country	Citing papers
United States	11
Switzerland	7
United Kingdom	5
China	5
South Korea	3
Sweden	3
Canada	3
Singapore	3
Germany	3
Italy	2
Belgium	2
Australia	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.

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	Deep convolutional networks in system identification	14	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Evaluating model calibration in classification	10	Dhanasar — Prong 2 (well-positioned)
Contribution 3	Automatic diagnosis of the 12-lead ECG using a deep neural network	9	Dhanasar — Prong 2 (well-positioned)