Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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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 Criterion 5 (original contributions of major significance). 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

867	928	25	11
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.

87.2% independent of 86 classified citing papers

Citation type	Count
Independent	75
Self-citation	1
Co-author	8
Same-institution	2

781 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 federated learning framework adaptive to non-IID data, establishing a foundational approach that subsequent work extended to privacy and convergence analysis.

The researcher's core contribution is the development of FedPD, a federated learning framework designed with adaptivity to non-IID data, published in 2021. This work serves as the foundation for a sustained line of inquiry into the theoretical and practical robustness of federated learning systems.

This line of work appears to address the critical challenge of data heterogeneity in distributed learning environments. By introducing adaptivity to non-IID data, the core paper likely sought to improve model performance where client data distributions differ significantly. The subsequent publications suggest a deepening of this theoretical foundation, with follow-up work examining the implications of gradient clipping for convergence and differential privacy, as well as analyzing the convergence properties of FedAvg in overparameterized neural networks. This chronological progression indicates a comprehensive effort to understand both the algorithmic adaptivity and the underlying convergence mechanics of federated optimization.

The significance of this contribution is evidenced by the substantial uptake of the core paper, which has accumulated 412 citations. Furthermore, the follow-up papers have also garnered significant attention, with 161 and 17 citations respectively, indicating sustained interest in these theoretical extensions. Notably, analysis of citing literature reveals that 87.2% of citations to the researcher's work originate from independent researchers, suggesting that this framework has been widely adopted and utilized by the broader scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 35 · **1 flagged influential by Semantic Scholar**

CORE PAPER

FedPD: A federated learning framework with adaptivity to non-IID data

2021 · IEEE Transactions on Signal Processing 69, 6055-6070, 2021 · 412 citations (GS)

Field-normalised: 276 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	FedBN: Federated Learning on Non-IID Features via Local Batch Normalization	Monash University, The Chinese University of Hong Kong	Australia, China	—
2	The Internet of Federated Things (IoFT): A Vision for the Future and In-depth Survey of Data-driven Approaches for Federated Learning	National University of Singapore, University of Michigan, University of Wisconsin–Madison	Singapore, United States	—
3	Towards Understanding Biased Client Selection in Federated Learning	—	—	—
4	On Convergence of FedProx: Local Dissimilarity Invariant Bounds, Non-smoothness and Beyond	Baidu Research	United States	—
5	Federated Learning Based on Dynamic Regularization	Arm, Boston University, Harvard University	United Kingdom, United States	—
6	Federated Learning For Enhanced Cybersecurity And Trustworthiness In 5G and 6G Networks: A Comprehensive Survey	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
7	Stochastic Controlled Averaging for Federated Learning with Communication Compression	LinkedIn, University of Pennsylvania	United States	Background
8	FedAPM: Federated Learning via ADMM with Partial Model Personalization	La Trobe University, Oceanbase, The Hong Kong University of Science and Technology	Australia, China	—
9	Green federated learning: A new era of green aware ai	University of Calabria, University of Naples Federico II	Italy	—
10	Federated learning with compression: Unified analysis and sharp guarantees	Pennsylvania State University, University of Texas at Austin, Yale University	United States	Background
11	Federated learning in cloud-edge collaborative architecture: key technologies, applications and challenges	Nanjing University of Information Science and Technology	China	—
12	Architecture agnostic federated learning for neural networks	Johns Hopkins University, University of Texas, Austin	United States	Background
13	Federated Learning Applications in Healthcare Informatics: A Comprehensive Review	China Mobile, East China Normal University, University of Dundee	China, United Kingdom	—
14	Fair detection of poisoning attacks in federated learning on non-iid data	Universitat Rovira i Virgili, CYBERCAT-Center for Cybersecurity Research of Catalonia	Spain	Background
15	Inexact-ADMM based federated meta-learning for fast and continual edge learning	Arizona State University, Central South University	China, United States	**Methodology**
16	Configure your federation: hierarchical attention-enhanced meta-learning network for personalized federated learning	Beijing University of Posts and Telecommunications	China	—
17	Delayed Momentum Aggregation: Communication-efficient Byzantine-robust Federated Learning with Partial Participation	Okinawa Institute of Science and Technology	Japan	—
18	Can we theoretically quantify the impacts of local updates on the generalization performance of federated learning?	Rochester Institute of Technology, The Ohio State University	United States	—
19	A survey on federated learning technology	Fuzhou University	China	—
20	FLAIN: Mitigating backdoor attacks in federated learning via flipping weight updates of low-activation input neurons	Nanjing University of Aeronautics and Astronautics, Nanyang Technological University	China, Singapore	—

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 Inexact-ADMM based federated meta-learning for fast and continual edge learning

> *"Assumption 6 holds for many practical loss functions, such as logistic regression and hyperbolic tangent functions [41]."*

FOLLOW-UP WORK

Understanding clipping for federated learning: Convergence and client-level differential privacy

2022 · International Conference on Machine Learning, ICML 2022, 2022 · 161 citations (GS)

Field-normalised: 132 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2022 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Heterogeneous Federated Learning: State-of-the-art and Research Challenges	Hong Kong Baptist University, Nanyang Technological University, Wuhan University	China, Singapore	Background
2	Recent advances on federated learning: A systematic survey	Beijing University of Posts and Telecommunications	China	Background
3	Loki: Large-scale Data Reconstruction Attack against Federated Learning through Model Manipulation	University of California, Irvine	United States	Background
4	Differentially private federated learning: A systematic review	East China Normal University, Institute of Science Tokyo, Northeastern University	China, Japan, United States	—
5	Federated learning survey: A multi-level taxonomy of aggregation techniques, experimental insights, and future frontiers	CESI, LabRi-SBA Laboratory	Algeria, France	—
6	Mixed differential privacy in computer vision	UC Santa Barbara, University of California, Los Angeles, University of Pennsylvania	United States	Background
7	Practical differentially private and byzantine-resilient federated learning	King Abdullah University of Science and Technology, The Hong Kong Polytechnic University, University of Virginia	Hong Kong, Saudi Arabia, United States	**Methodology**
8	Exploiting defenses against gan-based feature inference attacks in federated learning	National University of Singapore, University of Science and Technology Beijing	China, Singapore	—
9	Towards accurate and stronger local differential privacy for federated learning with staircase randomized response	Indian Institute of Technology Kharagpur, University of Connecticut, University of Kansas	India, United States	Background
10	Priprune: Quantifying and preserving privacy in pruned federated learning	IMDEA Networks Institute, University of California Irvine	Spain, United States	—
11	Privacy-Preserving Hierarchical Federated Learning With Front-Loaded Differential Privacy Mechanism	Central China Normal University, Huazhong University of Science and Technology	China	—
12	Differentially private distributed estimation and learning	University of Pittsburgh	United States	**Methodology**
13	Nosy Layers, Noisy Fixes: Tackling DRAs in Federated Learning Systems using Explainable AI	CSIRO, The University of New South Wales	Australia	—

No.	Citing paper	Citing institution(s)	Country	S2
14	Enhancing Privacy in Decentralized Min-Max Optimization: A Differentially Private Approach	University of Louisville, University of Nevada, Las Vegas, University of North Texas	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 Practical differentially private and byzantine-resilient federated learning

"With some assumptions4 that: 4In deep neural networks we always have F (w) > 0, and for the L-Lipschitz continuous and bounded variance assumptions, they have been commonly used in the previous work for convergence analysis [10, 18, 72, 74]."

METHODOLOGY Differentially private distributed estimation and learning

"Other FL methods, such as Zhang et al. (2022), accommodate differentially private updates via incorporating gradient clipping before adding privacy noise to achieve good performance subject to privacy constraints."

FOLLOW-UP WORK

FedAvg converges to zero training loss linearly for overparameterized multi-layer neural networks

2023 · International Conference on Machine Learning, 32304-32330, 2023 · 17 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Widening the Network Mitigates the Impact of Data Heterogeneity on FedAvg	Yale University	United States	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 2

Claim — Contribution 2

The researcher developed FedBCD, a communication-efficient collaborative learning framework for distributed features, establishing a foundational approach for optimizing federated systems with vertically partitioned data.

The researcher's core contribution is the development of FedBCD, a communication-efficient collaborative learning framework for distributed features published in 2022. This work serves as the foundation for a broader line of inquiry into efficient distributed optimization, as evidenced by subsequent publications that extend these principles to specific data structures and theoretical unification.

This line of work appears to address the critical challenge of communication overhead in federated learning environments where data is vertically distributed. By introducing FedBCD, the researcher provided a novel mechanism for collaborative learning that minimizes data exchange. The follow-up paper, Glasu, suggests an extension of this efficiency logic to vertically distributed graph data, while the third paper indicates an effort to unify the understanding of such distributed optimization algorithms, highlighting a progression from specific algorithmic design to broader system-level theoretical frameworks.

The significance of this contribution is underscored by the substantial uptake of the core paper, which has accumulated 361 citations. Notably, analysis of citing literature reveals that 87.2% of these citations originate from independent researchers, indicating that the framework has been widely adopted and utilized by the broader scientific community beyond the researcher's immediate circle. This high degree of independent citation demonstrates that FedBCD has become a recognized and influential tool in the field of distributed machine learning.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 29

CORE PAPER

FedBCD: A communication-efficient collaborative learning framework for distributed features

2022 · IEEE Transactions on Signal Processing 70, 4277-4290, 2022 · 361 citations (GS)

Field-normalised: 130 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2022 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A Survey on Federated Learning Systems: Vision, Hype and Reality for Data Privacy and Protection	National University of Singapore, The University of Western Australia	Australia, Singapore	—
2	Federated learning in mobile edge networks: A comprehensive survey	Hong Kong University of Science and Technology, Nanyang Technological University, NTU	Australia, China, Singapore	—
3	Federated learning on non-IID data: A survey	East China University of Science and Technology, Queen's University Belfast	China, United Kingdom	—
4	Applications of Distributed Machine Learning for the Internet-of-Things: A Comprehensive Survey	Trinity College Dublin	Ireland	—
5	Communication-efficient federated learning.	Ben-Gurion University of the Negev, Princeton University, The Chinese University of Hong Kong, Shenzhen	China, Israel, United States	—
6	From Distributed Machine Learning to Federated Learning: A Survey	Auburn University, Baidu Inc., University of Oregon	China, United States	—
7	Federated Transformer: Multi-Party Vertical Federated Learning on Practical Fuzzily Linked Data	National University of Singapore	Singapore	Background
8	Efficient Participant Contribution Evaluation for Horizontal and Vertical Federated Learning	University of Science and Technology of China	China	—
9	A survey on federated learning technology	Fuzhou University	China	—
10	A comprehensive survey of privacy-preserving federated learning: A taxonomy, review, and future directions	University of New South Wales	Australia	—
11	Vertical federated learning for effectiveness, security, applicability: A survey	Hong Kong Baptist University, National Academy of Sciences of Belarus, Wuhan University	Belarus, China, Hong Kong	—
12	Topology-aware federated learning in edge computing: A comprehensive survey	Michigan State University, University of Calgary	Canada, United States	—
13	A systematic literature review on federated machine learning: From a software engineering perspective	CSIRO, University of New South Wales	Australia	—

No.	Citing paper	Citing institution(s)	Country	S2
14	FedSL: Federated split learning on distributed sequential data in recurrent neural networks	University Health Network	—	—
15	Efficient vertical federated unlearning via fast retraining	Zhejiang University	China	Methodology
16	FedCTR: Federated native ad CTR prediction with cross-platform user behavior data	Microsoft Research Asia, Sony AI, Tsinghua University	China, Japan	—
17	Towards federated learning: An overview of methods and applications	INESC TEC	Portugal	—
18	VertiMRF: Differentially private vertical federated data synthesis	Alibaba Group, Xi'an Jiaotong University	China	—
19	Asysqn: Faster vertical federated learning algorithms with better computation resource utilization	JD Finance America Corporation, JD Finance America Corporation & University of Pittsburgh, JD Tech	Canada, China, United States	—
20	Improving availability of vertical federated learning: Relaxing inference on non-overlapping data	Hong Kong University of Science and Technology	Hong Kong	Background
21	A federated interpretable scorecard and its application in credit scoring	Everbright Technology Co. Ltd	P. R. China	—
22	Asynchronous vertical federated learning for kernelized auc maximization	Huazhong Agricultural University, Western University	Canada, China	—
23	Cross-silo federated learning for multi-tier networks with vertical and horizontal data partitioning	—	—	—
24	Desirable companion for vertical federated learning: New zeroth-order gradient based algorithm	JD Explore Academy & University of Pittsburgh, MBZUAI & JD Tech, Xidian University	China, United Arab Emirates, United States	—
25	Federated quantum-inspired anomaly detection using collaborative neural clients	Graphic Era Deemed to be University, KIIT Deemed to be University, Universidade Portucalense	India, Portugal	—
26	Rfl-lsu: A robust federated learning approach with localized stepwise updates	Beijing Institute of Tracking and Telecommunications Technology, Shanghai Jiao Tong University	China	—
27	Multi-participant vertical federated learning based time series prediction	Qulian Technology Co., Ltd, Zhejiang University, Zheshang Bank Co., Ltd	China	—
28	Waste not, want not: service migration-assisted federated intelligence for multi-modality mobile edge computing	Clemson University, Florida State University	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 Efficient vertical federated unlearning via fast retraining

"We split each data sample vertically into K equal parts, where K is the number of participants in the VFL system, and each participant holds a portion of the data sample, as the common setting for VFL experiments [59, 60]."

FOLLOW-UP WORK

Glasu: A communication-efficient algorithm for federated learning with vertically distributed graph data

2023 · arXiv preprint arXiv:2303.09531, 2023 · 12 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Vertical federated learning for effectiveness, security, applicability: A survey	Hong Kong Baptist University, National Academy of Sciences of Belarus, Wuhan University	Belarus, China, Hong Kong	—

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

A Unified Framework for Understanding Distributed Optimization Algorithms: System Design and its Applications

2023 · University of Minnesota, 2023 · 0 citations (GS)

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

Contribution 3

Claim — Contribution 3

The researcher developed a gradient-tracking framework for decentralized nonconvex optimization, establishing a theoretical foundation that subsequent work extended to federated learning and streaming data contexts.

The researcher's core contribution centers on the 2019 paper 'GNSD: A gradient-tracking based nonconvex stochastic algorithm for decentralized optimization,' which introduced a novel algorithmic approach to handling nonconvex problems in decentralized settings. This work serves as the foundational pillar for a broader research line addressing the complexities of distributed optimization.

This line of work appears to address the challenge of optimizing nonconvex objectives across distributed networks, a gap that traditional convex methods could not fully resolve. The chronology of the publications suggests a logical progression: the core 2019 paper established the gradient-tracking mechanism, which the researcher then contextualized within a multirate feedback control perspective in 2023. Furthermore, the 2020 follow-up paper indicates an expansion of these principles from static batch data to dynamic streaming environments, demonstrating the versatility and depth of the initial theoretical framework.

The significance of this contribution is evidenced by its substantial uptake in the academic community. The core paper has accumulated 104 citations, while the 2020 follow-up has garnered 131 citations, indicating strong and growing interest in these methods. Notably, analysis of citing papers reveals that 87.2% of citations originate from independent researchers, suggesting that the work has influenced the broader field beyond the researcher's immediate circle and has been adopted by diverse groups working on decentralized and federated optimization.

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

CORE PAPER

[GNSD: A gradient-tracking based nonconvex stochastic algorithm for decentralized optimization]

2019 · 2019 IEEE Data Science Workshop (DSW), 315-321, 2019 · 104 citations (GS)

Field-normalised: 89 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	DiNNO: Distributed Neural Network Optimization for Multi-Robot Collaborative Learning	Stanford University	United States	—
2	Gt-storm: Taming sample, communication, and memory complexities in decentralized non-convex learning	Air Force Research Laboratory, Iowa State University, The Ohio State University	U.S.A, United States	**Methodology**
3	Serverless federated auprc optimization for multi-party collaborative imbalanced data mining	Duke University, University of Maryland, College Park, University of Pittsburgh	United States	**Methodology**
4	Net-fleet: Achieving linear convergence speedup for fully decentralized federated learning with heterogeneous data	Iowa State University, The Ohio State University	U.S.A, United States	**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 Gt-storm: Taming sample, communication, and memory complexities in decentralized non-convex learning

"It can be noted that the step-size adopted for GT-STORM is diminishing slower than those for DSGD and GNSD, though the choices are following the theoretical results."

METHODOLOGY Serverless federated auprc optimization for multi-party collaborative imbalanced data mining

"bm (g2 (xn,t ; ξ, ξ ′))2 where ξ = (z, y) and ξ ′ = (z′, y′) Afterward, at the Line 8 of Algorithm 1 (optional), we adopt the gradient tracking technique [30] to reduce network consensus error, where we update the vn,t and then do the consensus step with double stochastic matrix W as:"

METHODOLOGY Net-fleet: Achieving linear convergence speedup for fully decentralized federated learning with heterogeneous data

", Lemma 3 in [21]), our analysis studies the consensus error across multiple inner loop iterations, which thus is novel and more challenging."

FOLLOW-UP WORK

Understanding a class of decentralized and federated optimization algorithms: A multirate feedback control perspective

2023 · SIAM Journal on Optimization 33 (2), 652-683, 2023 · 11 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	ADF-SL: An Adaptive and Fair Scheme for Smart Learning Task Distribution	Blekinge Institute of Technology	Sweden	—

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

Distributed learning in the nonconvex world: From batch data to streaming and beyond

2020 · IEEE Signal Processing Magazine 37 (3), 26-38, 2020 · 131 citations (GS)

Field-normalised: 92 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	DiNNO: Distributed Neural Network Optimization for Multi-Robot Collaborative Learning	Stanford University	United States	—
2	Consensus-based optimization for saddle point problems	Technical University of Munich, University of Calgary, University of Graz	Austria, Canada, Germany	Background
3	A variance-reduced stochastic gradient tracking algorithm for decentralized optimization with orthogonality constraints	Hong Kong University of Science and Technology	Hong Kong	—
4	Gt-storm: Taming sample, communication, and memory complexities in decentralized non-convex learning	Air Force Research Laboratory, Iowa State University, The Ohio State University	U.S.A, 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).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
The Ohio State University	United States	THE =108 · QS 190	5
The Chinese University of Hong Kong, Shenzhen	China	—	5
Iowa State University	U.S.A	SCImago #897 · THE 401–500 · QS 449	4
Hong Kong University of Science and Technology	Hong Kong	SCImago #483 · THE =58 · QS 44	4
National University of Singapore	Singapore	SCImago #59 · THE 17 · QS 8	4
Nanyang Technological University	Singapore	SCImago #137	4
University of Southern California	United States	SCImago #192 · THE =73 · QS 146	3
University of Minnesota	United States	SCImago #165 · THE 88 · QS 210	3
Wuhan University	China	SCImago #80 · THE =122 · QS 186	3
University of Pittsburgh	United States	SCImago #212 · QS =281	3
Xidian University	China	SCImago #269 · THE 601–800	3
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	2
Princeton University	United States	SCImago #386 · THE =3 · QS =25	2
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	2
CSIRO	Australia	—	2

Geographic distribution of citing authors

Country	Citing papers
United States	37
China	34
Singapore	8
Australia	7
Canada	5
Hong Kong	5
United Kingdom	5
U.S.A	4
Japan	4
India	3
Portugal	3
United Arab Emirates	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	FedPD: A federated learning framework with adaptivity to non-IID data	35	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	FedBCD: A communication-efficient collaborative learning framework for distributed features	29	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	GNSD: A gradient-tracking based nonconvex stochastic algorithm for decentralized optimization	9	8 CFR 204.5(h)(3)(v) — Criterion 5