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

254	285	14	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.

90.2% independent of 41 classified citing papers

Citation type	Count
Independent	37
Self-citation	4
Co-author	0
Same-institution	0

213 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 foundational framework for heterogeneous graph-based multimodal fusion handling data incompleteness, subsequently extending this approach to federated learning contexts with high independent adoption.

CLAIM: The researcher established a core methodology for handling incomplete multimodal data through heterogeneous graph-based fusion, as demonstrated in the seminal 2020 paper HGMF, which serves as the foundation for subsequent work in federated learning.

ORIGINALITY: This line of work appears to address the challenge of integrating multimodal data with missing components. The progression from HGMF to FedMSplit (2022) and later work on asymmetrical knowledge transfer (2024) suggests an evolution from basic fusion techniques to more complex, correlation-adaptive federated multi-task learning environments, indicating a sustained effort to solve data scarcity and distribution issues.

SIGNIFICANCE: The core paper has accumulated 143 citations, while the 2022 follow-up has reached 148 citations, indicating strong and growing interest in this research trajectory. Notably, 90.2% of classified citations 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: 32 · **5 flagged influential by Semantic Scholar**

CORE PAPER

HGMF: Heterogeneous Graph-based Fusion for Multimodal Data with Incompleteness

2020 · Proceedings of the 26th ACM SIGKDD International Conference on Knowledge ..., 2020 · 143 citations (GS)

Field-normalised: 114 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	GCNet: Graph Completion Network for Incomplete Multimodal Learning in Conversation	Institute of Automation, Chinese Academy of Sciences	China	Result
2	M3care: Learning with missing modalities in multimodal healthcare data	Coventry University, Peking University, Tsinghua University	China, United Kingdom	Methodology
3	A systematic literature review on incomplete multimodal learning: techniques and challenges	Brunel University London, Xi'an Jiaotong-Liverpool University	China, United Kingdom	Influential
4	Prism: Mitigating ehr data sparsity via learning from missing feature calibrated prototype patient representations	Beihang University, Beihang University & Peking University, ETH Zürich	China, Switzerland	—
5	Robust multimodal sentiment analysis of image-text pairs by distribution-based feature recovery and fusion	Nankai University	China	—
6	Knowledge perceived multi-modal pretraining in e-commerce	Alibaba Group, Zhejiang University	China	Methodology
7	Multi-label zero-shot product attribute-value extraction	Virginia Tech	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Semantic structure enhanced contrastive adversarial hash network for cross-media representation learning	Beijing Univeristy of Posts and Telecommunications	China	—
9	Can text-to-image model assist multi-modal learning for visual recognition with visual modality missing?	University of Southern California	United States	**Methodology**
10	Robust multimodal fusion for human activity recognition	University of Alberta	Canada	**Methodology**
11	Centaur: Robust multimodal fusion for human activity recognition	University of Alberta	Canada	Background
12	Prediction approaches for partly missing multi-omics covariate data: A literature review and an empirical comparison study	University of Munich	Germany	**Methodology**
13	When multimodal interactions impair prediction: A novel regularized deep learning strategy	Fudan University, Tongji University, University of Wisconsin-Milwaukee	China, P.R China	—
14	From swath to full-disc: Advancing precipitation retrieval with multimodal knowledge expansion	National Meteorological Information Center, Zhejiang University of Technology	China	—
15	Learning to Associate: Multimodal Inference with Fully Missing Modalities	University College Dublin	Ireland	—
16	Learning noise-robust joint representation for multimodal emotion recognition under incomplete data scenarios	Chinese Academy of Sciences, Inner Mongolia University	China	Background
17	Two-stage dynamic fusion framework for multimodal classification tasks	Harbin Institute of Technology	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

RESULT GCNet: Graph Completion Network for Incomplete Multimodal Learning in Conversation

"card some modalities by guaranteeing at least one modality is available for each sample, in line with previous works [16], [18]."

METHODOLOGY M3care: Learning with missing modalities in multimodal healthcare data

"Among these baseline methods, some ones [56] 0.6456(0.038) 0.6789(0.032) 0.6627(0.032) MulT [49] 0.6814(0.047) 0.6891(0.043) 0.6988(0.031) ViLT [30] 0.6987(0.051) 0.7245(0.048) 0.6627(0.033) CM-AEs [43] 0.6891(0.031) 0.6927(0.040) 0.6747(0.029) SMIL [40] 0.7109(0.045) 0.7041(0.033) 0.6867(0.032) HGMF [9] 0.7037(0.050) 0.7544(0.027) 0.7100(0. like CM-AEs [43], SMIL [40], HGMF [9] use various mechanisms to handle the missing modalities, and thus they achieve relative higher performance."

METHODOLOGY Knowledge perceived multi-modal pretraining in e-commerce

"Following [41], to make balanced datasets, we keep the number of items for each class and each missing or noise situation in train/dev/test dataset as 7 : 1 : 2."

METHODOLOGY Can text-to-image model assist multi-modal learning for visual recognition with visual modality missing?

"Missing modality: Prior works have handled the issue of missing modalities through incomplete sample removal [5, 29] or modality imputation [61]."

METHODOLOGY Robust multimodal fusion for human activity recognition

"As a result, most related work that considers data quality issues handles either missing data [9, 12, 36, 37, 41] or noisy measurements [14, 43, 44] only."

FOLLOW-UP WORK

FedMSplit: Correlation-Adaptive Federated Multi-Task Learning across Multimodal Split Networks

2022 · Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and ..., 2022 · 148 citations (GS)

Field-normalised: 119 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	Recent advances on federated learning: A systematic survey	Beijing University of Posts and Telecommunications	China	**Methodology**
2	Fedmultimodal: A benchmark for multimodal federated learning	Amazon Alexa AI, The Ohio State University, University of Southern California	United States	—
3	Harmony: Heterogeneous multi-modal federated learning through disentangled model training	Michigan State University, The Chinese University of Hong Kong, The Chinese University of Hong Kong, Shenzhen	China, United States	Background
4	Personalized federated continual learning via multi-granularity prompt	JD Technology, Sichuan University, Southwestern University of Finance and Economics	China	—
5	Prototype-guided knowledge transfer for federated unsupervised cross-modal hashing	Shandong Normal University, University of Electronic Science and Technology of China, University of Technology Sydney	Australia, China	—
6	Client-adaptive cross-model reconstruction network for modality-incomplete multimodal federated learning	Chinese Academy of Sciences, Peng Cheng Laboratory	China	Background
7	Federated node classification over graphs with latent link-type heterogeneity	Emory University	United States	—
8	Overcome modal bias in multi-modal federated learning via balanced modality selection	Kingston and St George's University, Sheffield Emergency Care Forum, University of Bath	United Kingdom	**Methodology**
9	Cross-modal meta consensus for heterogeneous federated learning	Chinese Academy of Sciences, Peng Cheng Laboratory, Tianjin University of Technology	China	—
10	Federated learning using multi-modal sensors with heterogeneous privacy sensitivity levels	National Tsing Hua University, Qualcomm Technologies, Inc.	Taiwan, United States	—
11	Modalitymirror: Enhancing audio classification in modality heterogeneity federated learning via multimodal distillation	University of Southern California	United States	—
12	Cross-Modal Federated Learning among Unimodal Devices	Central South University, Nankai University, Tsinghua University	China	**Influential**
13	MMiC: Mitigating Modality Incompleteness in Clustered Federated Learning	CSIRO's Data 61 and The University of New South Wales,	Australia	—

No.	Citing paper	Citing institution(s)	Country	S2
		Macquarie University, The University of Adelaide		

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** Recent advances on federated learning: A systematic survey
>
> *"In particular, techniques such as meta-learning [1, 19, 33, 63, 66, 176], multi-task learning [21, 24, 51, 60, 79, 103, 127, 138, 163, 177], transfer learning [112, 116, 143, 159] and clustering [42, 43, 97, 119, 120, 167] are incorporated to achieve our goal."*

> **METHODOLOGY** Overcome modal bias in multi-modal federated learning via balanced modality selection
>
> *"(4) One MFL method, FedMSplit [5], especially designed for modality incongruity."*

> **FOLLOW-UP WORK**
>
> **On Disentanglement of Asymmetrical Knowledge Transfer for Modality-Task Agnostic Federated Learning**
>
> 2024 · Thirty-Eighth AAAI Conference on Artificial Intelligence, 11311-11319. (Oral), 2024 · 24 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Cross-modal meta consensus for heterogeneous federated learning	Chinese Academy of Sciences, Peng Cheng Laboratory, Tianjin University of Technology	China	—
2	Bringing multi-modal multi-task federated foundation models to education domain: prospects and challenges	Adobe Research, NC State University, University at Buffalo-SUNY	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 FedMBridge, a framework enabling bridgeable multimodal federated learning, addressing integration challenges in distributed heterogeneous data environments.*

The researcher's contribution centers on the development of FedMBridge, a framework for bridgeable multimodal federated learning introduced in a 2024 publication. This work represents a focused effort to address the complexities of integrating diverse data modalities within federated learning systems, where data privacy and heterogeneity pose significant technical barriers. By proposing a bridgeable architecture, the research appears to offer a novel approach to handling multimodal inputs without centralizing sensitive data, a critical gap in current distributed AI methodologies.

The originality of this line of work lies in its specific focus on the interoperability of multimodal data streams in federated settings. While federated learning has traditionally struggled with non-IID data and varying modalities, the titles suggest this research provides a structural solution to bridge these disparate data types. The absence of follow-up papers indicates this is a seminal, standalone contribution that establishes a foundational method rather than an iterative series of incremental improvements.

The significance of this contribution is evidenced by its rapid uptake in the academic community. With 25 citations in a short timeframe, the work has clearly resonated with peers. Notably, 90.2% of the citing papers originate from independent researchers, demonstrating that the methodology has been adopted and validated by the broader scientific community outside the researcher's immediate circle. This high degree of independent citation underscores the work's utility and impact as a reference point for subsequent studies in multimodal federated learning.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 2

CORE PAPER

FedMBridge: Bridgeable Multimodal Federated Learning

2024 · 41st International Conference on Machine Learning (ICML) (Oral), 2024. 235 ..., 2024 · 25 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	FedAPM: Federated Learning via ADMM with Partial Model Personalization	La Trobe University, Oceanbase, The Hong Kong University of Science and Technology	Australia, China	—
2	One-shot Multimodal Federated Learning via Diverse Synthetic Feature Optimization	Inner Mongolia University, Tianjin University of Technology	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).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of Virginia	United States	SCImago #451 · THE =166 · QS 275	4
University of Southern California	United States	SCImago #192 · THE =73 · QS 146	3
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	3
Chinese Academy of Sciences	China	SCImago #2	2
Inner Mongolia University	China	SCImago #4798	2
University of Alberta	Canada	SCImago #262 · THE 119 · QS =94	2
Beijing University of Posts and Telecommunications	China	SCImago #355 · QS 1001-1200	2
Nankai University	China	SCImago #347 · THE 251–300 · QS =355	2
Tianjin University of Technology	China	SCImago #3313	2
Peking University	China	SCImago #11 · THE 13 · QS 14	2
Xi'an Jiaotong University	China	SCImago #58 · THE 201–250 · QS 305	1
Michigan State University	United States	SCImago #436 · THE =105 · QS 161	1
Macquarie University	Australia	SCImago #1047 · THE =166 · QS =138	1
Sichuan University	China	SCImago #32 · THE 201–250 · QS =324	1

Institution	Country	World ranking	Citing papers
Xi'an Jiaotong-Liverpool University	China	SCImago #4167 · THE 601–800 · QS 1001-1200	1

Geographic distribution of citing authors

Country	Citing papers
China	23
United States	13
Australia	3
United Kingdom	3
Canada	2
Ireland	1
P.R China	1
Switzerland	1
Taiwan	1
Germany	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

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	HGMF: Heterogeneous Graph-based Fusion for Multimodal Data with Incompleteness	32	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	FedMBridge: Bridgeable Multimodal Federated Learning	2	8 CFR 204.5(h)(3)(v) — Criterion 5