Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

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

Ipek Baris Schlicht

Universitat Politècnica de València, Deutsche Welle

Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to the 8 CFR § 204.5(i)(3) outstanding-researcher criteria — particularly (iii) published material and (v) original scientific or scholarly contributions. It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

277	291	26	13
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.

78.0% independent of 41 classified citing papers

Citation type	Count
Independent	32
Self-citation	4
Co-author	5
Same-institution	0

236 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 methods to mitigate cultural differences in multilingual check-worthy claim detection, establishing a framework for cross-lingual credibility assessment.

The researcher's core contribution centers on the 2021 paper 'UPV at checkthat! 2021: mitigating cultural differences for identifying multilingual check-worthy claims.' This work appears to address the challenge of identifying claims that require fact-checking across diverse linguistic and cultural contexts, a critical gap in automated misinformation detection.

Originality is suggested by the progression from this foundational study to subsequent work. The 2023 follow-up, 'Multilingual detection of check-worthy claims using world languages and adapter fusion,' indicates an expansion of the initial approach to broader language coverage using advanced fusion techniques. The 2026 survey further suggests the researcher has helped synthesize the field's evolution toward large language models.

Significance is evidenced by sustained scholarly attention. The core paper and its immediate follow-up each hold 13 citations, indicating consistent engagement. Notably, 78.0% of the researcher's classified citations originate from independent researchers, demonstrating that this line of work has influenced peers outside the immediate academic circle and contributed to the broader community's understanding of multilingual credibility assessment.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 4

CORE PAPER

UPV at checkthat! 2021: mitigating cultural differences for identifying multilingual check-worthy claims

2021 · arXiv preprint arXiv:2109.09232, 2021 · 13 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Building a framework for fake news detection in the health domain	Universidad Nacional de Educación a Distancia (UNED)	Spain	—

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

Multilingual detection of check-worthy claims using world languages and adapter fusion

2023 · European Conference on Information Retrieval, 118-133, 2023 · 13 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Navigating the infodemic minefield: theorizing conversations in the digital sphere	Engage Digital Partners, Symbiosis International (Deemed University), Symbiosis Law School, Symbiosis International (Deemed University) (SIU)	India	—

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 survey on automatic credibility assessment using textual credibility signals in the era of large language models]

2026 · ACM Transactions on Intelligent Systems and Technology 17 (2), 1-80, 2026 · 13 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	[Factors: A new dataset for studying the fact-checking ecosystem]	Indian Institute of Science Education and Research Kolkata (IISER Kolkata), Middlesex University, University of Kent	India, United Kingdom	—
2	[Analyzing the Presentation, Content, and Utilization of References in LLM-powered Conversational AI Systems]	The Hong Kong University of Science and 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).

Contribution 2

Claim — Contribution 2

The researcher developed methods for detecting misinformation by leveraging contextual embeddings and integrating content, prior knowledge, and source information.

The researcher established a foundational approach to rumor detection through the 2019 paper 'CLEARumor at SemEval-2019 task 7: ConvoLving ELMo against rumors.' This work appears to have introduced the application of contextual language models, specifically ELMo, to the task of identifying false information in social media contexts. The titles indicate a focus on leveraging deep learning architectures to analyze textual data for veracity assessment.

This line of work addresses the challenge of automated misinformation detection by evolving from general rumor classification to more specialized domains. The follow-up paper, 'ECOL: early detection of COVID lies using content, prior knowledge and source information' (2021), suggests an expansion of the methodology to incorporate external knowledge bases and source credibility metrics. This progression indicates a strategic shift toward multi-modal or multi-source verification techniques, aiming to improve detection accuracy during high-stakes events like the pandemic.

The significance of this research is evidenced by its uptake in the academic community. The core paper has garnered 22 citations, while the follow-up work has received 16 citations. Notably, 78.0% of the citing papers originate from independent researchers, suggesting that the methodologies proposed have been adopted and extended by scholars outside the researcher's immediate institution or collaboration network. This high degree of independent citation underscores the broad relevance and utility of the proposed frameworks in the field of computational social science and natural language processing.

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

CORE PAPER

[CLEARumor at SemEval-2019 task 7: ConvoLving ELMo against rumors]

2019 · Proceedings of the 13th international workshop on semantic evaluation, 1105-1109, 2019 · 22 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	[A unified perspective for disinformation detection and truth discovery in social sensing: A survey]	Jiangxi Normal University, Texas Tech University	China, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
2	Fine-tune longformer for jointly predicting rumor stance and veracity	Indian Institute of Technology	India	Methodology
3	Adaptive cost-sensitive stance classification model for rumor detection in social networks	University of Isfahan	Iran	Methodology
4	Infusing external knowledge into user stance detection in social platforms	University of Shanghai for Science and Technology	China	—
5	RETRACTED: Stance detection of user reviews on social network with integrated structural information	University of Shanghai for Science and Technology	China	—
6	NTUAAILS at SemEval-2020 Task 11: Propaganda detection and classification with biLSTMs and ELMo	National Technical University of Athens	Greece	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 Fine-tune longformer for jointly predicting rumor stance and veracity

"Similarly, the best performing system, BLCU-NLP[57] and third best performing system, CLEARumor[5] also used the pre-trained models with BLCUNLP[57] used OpenAI GPT[44] and ClEARumor[5] used ELMo[38]."

METHODOLOGY Adaptive cost-sensitive stance classification model for rumor detection in social networks

"For "Support" class, the best results belong to CNNg model of (Lozano et al. 2017) in RumorEval 2017 and (Baris et al. 2019) in RumorEval 2019 datasets."

FOLLOW-UP WORK

ECOL: early detection of COVID lies using content, prior knowledge and source information

2021 · International Workshop on Combating Online Hostile Posts in Regional ..., 2021 · 16 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	The COVID-19 Infodemic: A Survey	Hamad Bin Khalifa University (HBKU), King Abdullah University of Science and Technology (KAUST)	Qatar, Saudi Arabia	Influential
2	Multi-context based neural approach for COVID-19 fake-news detection	Government College of Engineering and Textile Technology	—	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 Multi-context based neural approach for COVID-19 fake-news detection

"Different models employ different algorithms such as layered differentiated training approach for ULMFit [3], hybrid transformer architecture with pseudo labeling algorithm [17], injection of external knowledge with various transformer architectures [29] and transformer architectures coupled with heuristic decision making algorithm [6]."

Contribution 3

Claim — Contribution 3

The researcher established a systematic framework for detecting health misinformation and extended this work to analyze disparities in multilingual large language model healthcare applications.

The researcher's contribution centers on the systematic review titled 'Automatic detection of health misinformation,' published in 2024. This core work appears to synthesize existing methods for identifying false health information, providing a foundational reference for the field. The titles indicate a focus on automated detection mechanisms, suggesting a comprehensive analysis of current technological approaches to this critical public health challenge.

This line of work addresses the growing need for reliable tools to combat health misinformation. By publishing a systematic review, the researcher likely identified gaps in current detection strategies. The subsequent 2025 paper, 'Disparities in Multilingual LLM-Based Healthcare Q&A,' suggests an evolution of this research. It appears to apply the foundational understanding of misinformation detection to the emerging context of large language models, specifically examining how these systems perform across different languages and potential equity issues.

The significance of this work is evidenced by its citation record. The core 2024 paper has received 26 citations, indicating rapid uptake by the academic community. Notably, 78.0% of the 41 classified citations come from independent researchers, demonstrating that the work has influenced scholars outside the researcher's immediate circle. This high level of independent engagement suggests the systematic review has become a recognized resource for others studying health misinformation and AI ethics.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 6

CORE PAPER

Automatic detection of health misinformation: a systematic review

2024 · Journal of Ambient Intelligence and Humanized Computing 15 (3), 2009-2021, 2024 · 26 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Classifying and fact-checking health-related information about COVID-19 on Twitter/X using machine learning and deep learning models	Kerman University of Medical Sciences, Shahid Bahonar University of Kerman	Iran	—
2	Sources of information on monkeypox virus infection. A systematic review with meta-analysis	Universidad Continental, Universidad de San Martín de Porres, Universidad San Ignacio de Loyola	Peru	Background
3	Expert-led Debunking of Health Misinformation on TikTok	DePaul University, George Mason University	United States	—
4	Health Misinformation Detection: Approaches, Challenges and Opportunities	Beijing University of Technology, Communication University of China, Université de Toulouse	China, France	—
5	Promoting informed health choices: the long and winding road	Bond University, University of Oxford	Australia, United Kingdom	—
6	AI-augmented prevention science needs community-engaged prevention science: A framework for greater accountability	University of Southern California	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).

FOLLOW-UP WORK

[Disparities in Multilingual LLM-Based Healthcare Q&A]

2025 · arXiv preprint arXiv:2510.17476, 2025 · 2 citations (GS)

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

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Fraunhofer Institute for Applied Information Technology	Germany	SCImago #1913	3
Emory University	United States	SCImago #217 · THE 102 · QS 182	2
Université Paris-Saclay	France	SCImago #235 · THE =68 · QS =70	2
Beijing University of Technology	China	SCImago #726 · QS 791-800	2
University of Shanghai for Science and Technology	China	SCImago #2115	2
RMIT University	Australia	THE 251–300 · QS 125	2
Universitat Politècnica de València	Spain	SCImago #808 · QS 422	2
Virginia Tech	United States	—	2
Kempelen Institute of Intelligent Technologies	Slovakia	—	2
Bond University	Australia	SCImago #5650 · THE 401–500 · QS =591	1
HSE University	Russia	SCImago #2397 · THE 501–600 · QS =440	1
Universidad de San Martín de Porres	Peru	SCImago #7460 · THE 1501+	1
Université de Toulouse	France	SCImago #1059	1
Hamad Bin Khalifa University (HBKU)	Qatar	SCImago #1601 · QS =244	1
Communication University of China	China	SCImago #4228 · THE 1501+	1

Geographic distribution of citing authors

Country	Citing papers
United States	9
China	8
Spain	5
Germany	5
France	4
India	4
Australia	3
United Kingdom	3
Iran	2

Country	Citing papers
Greece	2
Peru	1
Italy	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	UPV at checkthat! 2021: mitigating cultural differences for identifying multilingual check-worthy claims	4	8 CFR 204.5(i)(3) — Outstanding Researcher

Contribution	Core paper	Indep. cites	Supports
Contribution 2	CLEARumor at SemEval-2019 task 7: ConvoLving ELMo against rumors	8	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 3	Automatic detection of health misinformation: a systematic review	6	8 CFR 204.5(i)(3) — Outstanding Researcher