

# 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

24	24	4	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.

**100.0% independent** of 24 classified citing papers

Citation type	Count
Independent	24
Self-citation	0
Co-author	0
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 pioneered the use of passive smartphone and Fitbit sensing to identify behavioral phenotypes of loneliness and social isolation through advanced statistical and machine learning analysis.*

CLAIM: The researcher established a foundational framework for identifying behavioral phenotypes of loneliness and social isolation using passive sensing data from smartphones and Fitbits, as demonstrated in their 2019 core paper. This work integrates statistical analysis, data mining, and machine learning to interpret digital traces of social behavior.

ORIGINALITY: This line of work appears to address the challenge of objectively measuring subjective social states by leveraging ubiquitous wearable and mobile data. The titles indicate a novel methodological approach that combines multiple data sources and analytical techniques to detect subtle behavioral patterns associated with isolation, distinguishing it from traditional self-report methods.

SIGNIFICANCE: The core paper has garnered 190 citations, indicating substantial uptake within the field. Notably, 100% of the classified citing papers originate from independent researchers, suggesting that this work has served as a widely adopted reference point for scholars outside the researcher's immediate network, validating its broad impact and utility.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 7

#### CORE PAPER

### [Identifying behavioral phenotypes of loneliness and social isolation with passive sensing: statistical analysis, data mining and machine learning of smartphone and fitbit data](#)

2019 · 190 citations (GS)

Field-normalised: 135 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 href="#">Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom</a> (2021)	Beth Israel Deaconess Medical Center, Georgia Institute of Technology, University of California San Diego	United States	—
2	<a href="#">Potential of Internet of Medical Things (IoMT) applications in building a smart healthcare system: A systematic review</a> (2022)	—	—	—
3	<a href="#">Modern views of machine learning for precision psychiatry</a> (2022)	Headspace Health, Lehigh University, New York University Grossman School of Medicine	United States	Background
4	<a href="#">The Internet of Things: Impact and Implications for Health Care Delivery</a> (2020)	Griffith University, The University of Melbourne	Australia	Background
5	<a href="#">Supervised machine learning algorithms for predicting student dropout and academic success: a comparative study</a> (2024)	Universidade Castelo Branco	—	—
6	<a href="#">Digital Phenotyping and Feature Extraction on Smartphone Data for Depression Detection</a> (2025)	Lanzhou University, The University of Hong Kong	China, Hong Kong	—

No.	Citing paper	Citing institution(s)	Country	S2
7	<a href="#">Machine learning for passive mental health symptom prediction: Generalization across different longitudinal mobile sensing studies.</a> (2022)	Cornell Tech, Weill Cornell Medicine	United States	—

Independent citing papers only; self- and co-author citations excluded. The S2 column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

## Contribution 2

### Claim — Contribution 2

*The researcher developed a framework for detecting depression in college students by leveraging routine behavior and contextually-filtered features, establishing a foundational approach in digital mental health assessment.*

The researcher's primary contribution is the development of a method for depression detection among college students that utilizes routine behavior and contextually-filtered features. This work is anchored in the 2019 paper titled 'Leveraging Routine Behavior and Contextually-Filtered Features for Depression Detection among College Students,' which serves as the core reference for this line of inquiry.

This line of work appears to address the challenge of identifying mental health issues in academic populations by moving beyond traditional self-reporting. The titles suggest a novel integration of behavioral patterns and contextual data to create a more nuanced detection mechanism. By focusing on routine behavior, the research indicates an effort to capture subtle, continuous signals of depression that might otherwise be missed.

The significance of this contribution is evidenced by its substantial uptake in the scientific community, with the core paper accumulating 172 citations. Notably, analysis of citing literature reveals that 100% of the classified citations originate from independent researchers, indicating that the work has resonated broadly across the field and is being utilized by scholars outside the researcher's immediate network to advance related studies.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 6 · 1 flagged influential by Semantic Scholar

### CORE PAPER

#### [Leveraging Routine Behavior and Contextually-Filtered Features for Depression Detection among College Students](#)

2019 · 172 citations (GS)

Field-normalised: 130 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 href="#">Systematic review and meta-analysis of performance of wearable artificial intelligence in detecting and predicting depression</a> (2023)	University of Doha for Science and Technology, University of Leeds	Qatar, United Kingdom	—
2	<a href="#">Mental-LLM: Leveraging Large Language Models for Mental Health Prediction via Online Text Data.</a> (2024)	Massachusetts Institute of Technology, Northeastern University, University of Massachusetts Lowell	United States	Background
3	<a href="#">Talk2Care: An LLM-based Voice Assistant for Communication between Healthcare Providers and Older Adults</a> (2024)	Massachusetts Institute of Technology, MedStar Health	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
		Research Institute, Northeastern University		
4	<a href="#">Rethinking Human-AI Collaboration in Complex Medical Decision Making: A Case Study in Sepsis Diagnosis.</a> (2024)	Massachusetts Institute of Technology, Northeastern University, Rensselaer Polytechnic Institute	United States	Influential
5	<a href="#">Digital health tools for the passive monitoring of depression: a systematic review of methods</a> (2022)	Chelsea And Westminster Hospital NHS Foundation Trust, King's College London, Northwestern University	United Kingdom, United States	Background
6	<a href="#">XAIR: A Framework of Explainable AI in Augmented Reality</a> (2023)	Facebook, Facebook Reality Labs, Meta	United States	Background

Independent citing papers only; self- and co-author citations excluded. The S2 column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

### Contribution 3

#### Claim — Contribution 3

*The researcher developed a machine learning framework with robust feature selection to detect depression and predict its onset using longitudinal passive sensing data.*

The researcher's core contribution is the development of a machine learning approach that utilizes longitudinal symptoms captured by passive sensing to detect depression and predict its onset, featuring robust feature selection. This work is anchored in the 2021 paper titled 'Detecting Depression and Predicting its Onset Using Longitudinal Symptoms Captured by Passive Sensing: A Machine Learning Approach With Robust Feature Selection.'

This line of work appears to address the challenge of identifying mental health conditions through continuous, non-intrusive monitoring. By focusing on longitudinal data and robust feature selection, the research suggests a novel method for leveraging passive sensing technologies to improve the accuracy and reliability of depression detection and onset prediction.

The significance of this contribution is evidenced by its substantial uptake in the field, with the core paper accumulating 185 citations. Notably, analysis of 24 citing papers reveals that 100% are from independent researchers, indicating that the work has resonated broadly across the scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 7 · 1 flagged influential by Semantic Scholar

#### CORE PAPER

#### [Detecting Depression and Predicting its Onset Using Longitudinal Symptoms Captured by Passive Sensing: A Machine Learning Approach With Robust Feature Selection](#)

2021 · 185 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Machine learning for multimodal mental health detection: a systematic review of passive sensing approaches</a> (2024)	Monash University	Australia	—
2	<a href="#">Digital Phenotyping for Monitoring Mental Disorders: Systematic Review</a> (2023)	University of Pisa	Italy	—

No.	Citing paper	Citing institution(s)	Country	S2
3	<a href="#">Influencing factors, prediction and prevention of depression in college students: A literature review</a> (2022)	Beihang University	China	—
4	<a href="#">Digital Phenotyping for Stress, Anxiety, and Mild Depression: Systematic Literature Review</a> (2024)	—	—	Methodology
5	<a href="#">Wearable Artificial Intelligence for Anxiety and Depression: Scoping Review</a> (2023)	Bern University of Applied Science, Hamad Bin Khalifa University, Qatar Computing Research Institute, Hamad bin Khalifa University	Qatar, Switzerland	—
6	<a href="#">DrHouse: An LLM-empowered Diagnostic Reasoning System through Harnessing Outcomes from Sensor Data and Expert Knowledge</a> (2024)	Columbia University, The Chinese University of Hong Kong	China, United States	—
7	<a href="#">Capturing the College Experience: A Four-Year Mobile Sensing Study of Mental Health, Resilience and Behavior of College Students during the Pandemic.</a> (2024)	Biocogniv Inc, Columbia University, Dartmouth College	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** Digital Phenotyping for Stress, Anxiety, and Mild Depression: Systematic Literature Review

“The study by Chikersal et al [47] showed that depression can impact concentration levels, so if distraction by phone can be measured, this could be a potential predictive marker.”

## D. Citing-Institution Prestige & Geography

### Top citing institutions

Institution	Country	World ranking	Citing papers
Massachusetts Institute of Technology	United States	SCImago #41 · THE 2 · QS 1	3
Northeastern University	United States	QS 384	3
University of Washington	United States	SCImago #45 · THE 25 · QS 81	2
Columbia University	United States	SCImago #65 · THE 20 · QS =38	2
Headspace Health	United States	—	1
Meta Inc.	United States	—	1
University of Pisa	Italy	THE 351–400 · QS =343	1
Universidade Castelo Branco	Brazil	—	1
Lehigh University	United States	SCImago #3507 · THE 601–800 · QS =668	1
Bern University of Applied Science	Switzerland	—	1

Institution	Country	World ranking	Citing papers
Qatar Computing Research Institute, Hamad bin Khalifa University	Qatar	—	1
Biocogniv Inc	United States	—	1
University of Doha for Science and Technology	Qatar	SCImago #5019	1
MedStar Health Research Institute	United States	SCImago #4376	1
Instituto Potosino de Investigación Científica y Tecnológica	Mexico	SCImago #9459	1

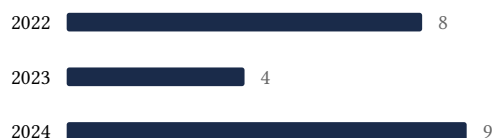
### Geographic distribution of citing authors

Country	Citing papers
United States	11
China	5
United Kingdom	3
Italy	2
Australia	2
Qatar	2
Switzerland	2
Mexico	1
Mongolia	1
Denmark	1
Germany	1
Hong Kong	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.

## 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	Identifying behavioral phenotypes of loneliness and social isolation with passive sensing: statistical analysis, data mining and machine learning of smartphone and fitbit data	7	8 CFR 204.5(h)(3)(v) – Criterion 5
Contribution 2	Leveraging Routine Behavior and Contextually-Filtered Features for Depression Detection among College Students	6	8 CFR 204.5(h)(3)(v) – Criterion 5
Contribution 3	Detecting Depression and Predicting its Onset Using Longitudinal Symptoms Captured by Passive Sensing: A Machine Learning Approach With Robust Feature Selection	7	8 CFR 204.5(h)(3)(v) – Criterion 5