Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Artificial Intelligence in Autoimmune Neurological Disorders: A Bibliometric Analysis and Research Landscape

Nikhila Kommala

nikhilakommala8@gmail.com

Guntur Medical College https://orcid.org/0009-0008-2127-7048

Research Article

Keywords: artificial intelligence; machine learning; deep learning; multiple sclerosis; autoimmune neurology; neuroimaging; bibliometrics; multimodal

Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11706986/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Artificial Intelligence in Autoimmune Neurological Disorders: A Bibliometric Analysis and Research Landscape

Nikhila K[1]*

[1] Guntur Medical College, Dr. NTR University of Health Sciences, Guntur, Andhra Pradesh, India

* Corresponding author: nikhilakommala8@gmail.com · ORCID: [to be added]

Preprint — draft for OSF / Research Square. Prepared November 2026. Not peer reviewed.

Abstract

Background. Artificial intelligence (AI) and machine learning are being applied rapidly across autoimmune neurological disorders, but the overall shape of this literature — which disorders, data modalities and methods dominate, and where evidence is absent — has not been quantified.

Objective. To map the published research landscape of AI in autoimmune neurological disorders through a bibliometric analysis, and to identify the field's concentrations and gaps.

Methods. PubMed/MEDLINE was searched in November 2026 using a title/abstract strategy combining terms for autoimmune neurological disorders (multiple sclerosis [MS], neuromyelitis optica spectrum disorder [NMOSD], myelin-oligodendrocyte-glycoprotein antibody-associated disease [MOGAD], autoimmune encephalitis, autoimmune epilepsy, paraneoplastic neurological syndromes) with artificial-intelligence and machine-learning terms, limited to 2015–2026. Records were exported and analysed programmatically for annual output, leading journals, authorship, open-access status, and disorder-, modality- and method-level focus (title-level tagging).

Results. 1,455 records were analysed. Annual output rose from 10 (2015) to 270 (2025), with 2026 already at 319 ahead-of-print records; output grew approximately 12-fold between 2015–2018 and 2022–2025. The literature was dominated by multiple sclerosis (883 records, 60.7%), with all other disorders comparatively rare (NMOSD 45; autoimmune encephalitis 26; MOGAD 11; paraneoplastic 1). Magnetic resonance imaging was the dominant data modality (517 records, 35.5%), whereas electroencephalography (9), genomics (25) and cerebrospinal-fluid biomarkers (83) were seldom addressed. Only 33 records (2.3%) described multimodal or data-fusion approaches. Deep learning (259) had overtaken classical machine learning (226). Work was distributed across 463 journals (led by Multiple Sclerosis and Related Disorders, n=84); 63.9% of records were open access.

Conclusions. Research on AI in autoimmune neurology is expanding steeply but is heavily concentrated on multiple sclerosis and MRI. Rarer disorders, electrophysiological, fluid-biomarker and genomic data, and genuine multimodal integration remain markedly under-explored — defining clear priorities for future work.

Keywords: *artificial intelligence; machine learning; deep learning; multiple sclerosis; autoimmune neurology; neuroimaging; bibliometrics; multimodal.*

1 Introduction

Autoimmune neurological disorders — including multiple sclerosis (MS), neuromyelitis optica spectrum disorder (NMOSD), myelin-oligodendrocyte-glycoprotein antibody-associated disease (MOGAD), the autoimmune encephalitides, autoimmune epilepsy and paraneoplastic neurological syndromes — are

diagnostically demanding conditions in which clinical, imaging, electrophysiological, fluid-biomarker and genetic information must be integrated, often from small and heterogeneous patient populations. Over the last decade, artificial intelligence (AI) and machine learning (ML), and in particular deep learning, have been applied with increasing intensity to these data, from lesion segmentation and diagnostic classification to prognosis and treatment-response prediction [1–3].

Despite this growth, the overall structure of the literature has not been quantified. It is not clear which disorders and which data modalities have attracted most attention, which AI methods predominate, or — critically — where evidence is sparse or absent. Bibliometric analysis, which applies quantitative methods to the metadata of a body of publications, is well suited to answering such questions and to making the gaps in a field visible. We therefore performed a bibliometric analysis of AI in autoimmune neurological disorders, with two aims: to characterise the growth, venues and thematic composition of the field; and to identify its concentrations and whitespace, particularly with respect to under-studied disorders, modalities and multimodal integration.

2 Methods

2.1 Data source and search strategy

PubMed/MEDLINE was searched in November 2026. A title/abstract ([tiab]) strategy combined two concept blocks with the Boolean operator AND: (i) autoimmune neurological disorders (“multiple sclerosis”, “neuromyelitis optica”, NMOSD, MOGAD, “MOG antibody”, “autoimmune encephalitis”, “autoimmune epilepsy”, “paraneoplastic neurological”); and (ii) artificial intelligence and machine learning (“artificial intelligence”, “machine learning”, “deep learning”, “neural network(s)”, radiomics, convolutional, “natural language processing”, “data fusion”). The search was limited to 2015–2026. The full query is reproduced in the Appendix.

2.2 Screening and inclusion

All records returned by the search were exported from PubMed and included in the descriptive bibliometric analysis; no manual exclusion of individual studies was performed, consistent with a landscape-level analysis. A small number of records carried an earlier electronic-publication year (2014); these were retained. Records for the current year (2026) include ahead-of-print and early-access items and therefore represent a partial year.

2.3 Data extraction

Records were parsed programmatically (custom Python scripts) to extract, for each item, the publication year, journal, author list, digital object identifier (DOI), PubMed and PubMed Central identifiers (PMID, PMCID), and title. Open-access status was approximated by the presence of a PMCID. Disorder, data-modality and AI-method focus were assigned by case-insensitive keyword matching against record titles; because titles do not always name the modality or method used, these counts are conservative lower bounds of true coverage.

2.4 Bibliometric analysis

We quantified annual publication output and growth, the most productive journals, the number of contributing authors and mean authorship, and the distribution of records across disorders, data modalities

and AI-method families. Title terms were tokenised to describe dominant themes. Analyses were performed in Python; results are reported descriptively [13,14].

2.5 Ethics

This study used only previously published bibliographic metadata and did not involve human participants, patient-level data or interventions; ethics-committee approval was therefore not required.

3 Results

3.1 Publication output and growth

The search yielded 1,455 records. Annual output increased steeply across the study period, from 10 publications in 2015 to 270 in 2025; the partial year 2026 already contained 319 ahead-of-print records (Figure 1a). Output grew approximately 12-fold between the first (2015–2018; 67 records) and most recent complete (2022–2025; 782 records) four-year windows, indicating sustained and accelerating activity rather than a plateau.

3.2 Leading journals and venues

The 1,455 records were distributed across 463 journals, reflecting a broad and cross-disciplinary field spanning neurology, neuroimaging, immunology and biomedical computing. The most productive venue was Multiple Sclerosis and Related Disorders (n=84), followed by Frontiers in Neuroscience (41), NeuroImage: Clinical (40) and Frontiers in Neurology (39) (Figure 1b; Table 1). Medical-imaging and computing venues (NeuroImage, Medical Image Analysis, Computers in Biology and Medicine) featured prominently, underscoring the imaging- and methods-heavy character of the field.

3.3 Disorder focus

The literature was overwhelmingly concentrated on multiple sclerosis, which appeared in 883 record titles (60.7%). All other autoimmune neurological disorders were addressed far less frequently: NMOSD in 45 titles, autoimmune encephalitis in 26, MOGAD in 11 and paraneoplastic neurological syndromes in just 1 (Figure 1c). This distribution demonstrates that AI research in this domain is, in practice, largely AI research in MS.

3.4 Data-modality emphasis

A parallel concentration was seen across data modalities. Magnetic resonance imaging dominated, appearing in 517 record titles (35.5%), whereas cerebrospinal-fluid and fluid biomarkers (83), clinical/electronic-health-record data (32), genomics (25) and — most strikingly — electroencephalography (9) were rarely the focus (Figure 1d). Only 33 records (2.3%) described multimodal or data-fusion approaches that combine two or more of these data types, indicating that integrative modelling remains nascent.

3.5 AI methods and themes

Among records whose titles named a method family, deep learning (259) had overtaken classical machine learning (226), with radiomics (48) and natural-language processing (16) less common; a small but emerging set of records (14) referenced large-language or foundation models. Dominant title themes mirrored the modality findings, centred on lesion segmentation, diagnosis, classification, disease-progression prediction and magnetic-resonance imaging.

3.6 Authorship and open access

The corpus involved 7,954 contributing authors, with a mean of 8.7 authors per record, consistent with multidisciplinary team science. Open access was high: 930 records (63.9%) were available through PubMed Central.

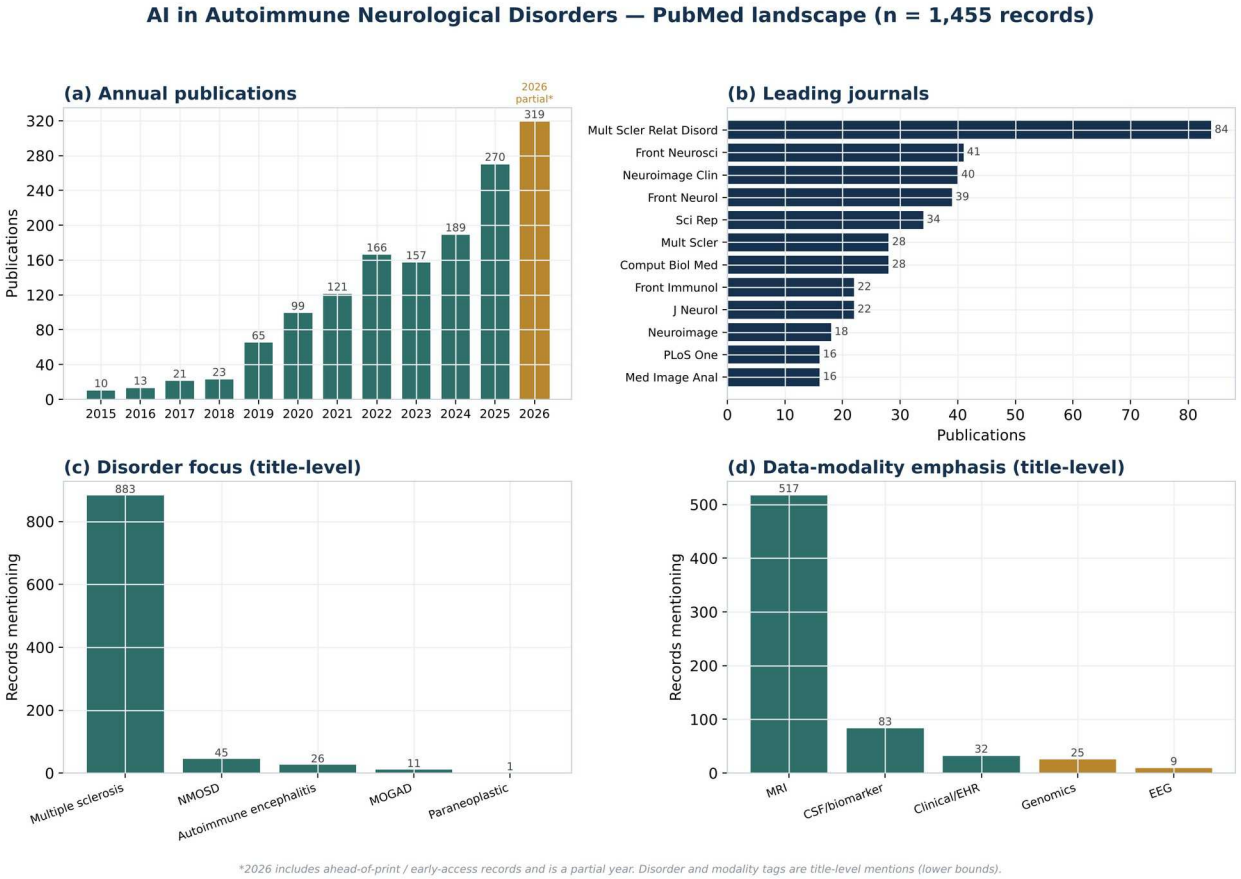


Figure 1. *Research landscape of artificial intelligence in autoimmune neurological disorders (PubMed, n=1,455). (a) Annual publications, 2015–2026 (2026 partial, ahead-of-print, shown in amber). (b) Twelve most productive journals. (c) Disorder focus and (d) data-modality emphasis, by title-level keyword tagging (conservative lower bounds).*

Table 1. Most productive journals (top 12).

Journal	Records
Multiple Sclerosis and Related Disorders	84
Frontiers in Neuroscience	41
NeuroImage: Clinical	40
Frontiers in Neurology	39
Scientific Reports	34
Multiple Sclerosis Journal	28

Computers in Biology and Medicine	28
Frontiers in Immunology	22
Journal of Neurology	22
NeuroImage	18
PLOS ONE	16
Medical Image Analysis	16

Table 2. Disorder, modality and method focus (title-level counts; lower bounds).

Disorder / modality / method	Records	% of 1,455
Multiple sclerosis	883	60.7%
NMOSD	45	3.1%
Autoimmune encephalitis	26	1.8%
MOGAD	11	0.8%
Paraneoplastic	1	0.1%
— MRI	517	35.5%
— CSF / fluid biomarkers	83	5.7%
— Clinical / EHR	32	2.2%
— Genomics	25	1.7%
— EEG	9	0.6%
Deep learning	259	17.8%
Classical ML	226	15.5%
Radiomics	48	3.3%
NLP	16	1.1%
Multimodal / fusion	33	2.3%

4 Discussion

This bibliometric analysis of 1,455 publications shows that AI research in autoimmune neurological disorders is expanding rapidly but is strikingly concentrated. Three concentrations stand out: by disorder, the field is dominated by multiple sclerosis; by modality, it is dominated by MRI; and by integration, it remains almost entirely unimodal, with only 2.3% of records describing multimodal or data-fusion methods.

The dominance of MS is understandable — MS is the most prevalent of these conditions, has internationally standardised MRI criteria and large imaging cohorts, and is supported by dedicated journals and consortia [1,3,5]. Yet the consequence is that AI development is weakest precisely where diagnosis is often hardest. NMOSD and MOGAD are important MS mimics with different treatment and prognosis, and their radiological and serological separation from MS is a recognised clinical challenge that a handful of radiomics and deep-learning studies have begun to address [5,6,16]; the autoimmune encephalitides frequently present with normal or subtle MRI and depend heavily on electroencephalography and cerebrospinal-fluid antibodies [7,17]. The scarcity of AI work on these disorders — and the near-absence of work using EEG (9 records) or genomic data (25 records) [8,9,18] — suggests that current models are concentrated on the data that are easiest to obtain rather than the data that are most diagnostically decisive.

The clearest gap is multimodal integration. Clinicians diagnosing autoimmune neurological disease rarely rely on a single data stream; they combine imaging, electrophysiology, fluid biomarkers, genetic risk and the clinical picture. Yet only 33 of 1,455 records attempted to fuse modalities, and early examples remain largely confined to MS [10,11]. Fluid-biomarker work, including cerebrospinal-fluid and blood neurofilament light chain, is similarly under-represented despite its prognostic value [11,12]. Genuine multimodal, genomics-inclusive modelling — particularly for the rarer, harder-to-diagnose disorders — is therefore the field's most prominent whitespace and a priority for future research.

For researchers, these findings argue for deliberately directing effort toward under-served disorders and modalities, for multi-centre data sharing to overcome the small sample sizes that constrain rare-disease modelling, and for integrative study designs. For clinicians, the results are a reminder that the maturity of AI evidence is highly uneven across the conditions they treat. As models move toward deployment, attention to responsible-AI practice — transparent reporting, external validation [21] and equity — will be essential [19,20], and adherence to AI-specific reporting standards should become routine.

5 Limitations

This analysis has several limitations. First, it is based on a single database (PubMed/MEDLINE); although PubMed provides comprehensive biomedical coverage, the inclusion of Scopus or Web of Science would capture additional records and enable citation-based metrics, which were not available here. Second, disorder-, modality- and method-level tagging was performed at the title level and is therefore a conservative lower bound; abstract- and MeSH-based tagging would raise these counts, though the relative pattern is expected to be robust. Third, author-affiliation and country-level analyses, and keyword co-occurrence mapping, were not possible from the exported record format and are planned as an extension using a MEDLINE-format export. Fourth, the 2026 figure is a partial, ahead-of-print year and should not be read as a complete annual count. Finally, bibliometric methods describe the structure of a literature but do not assess the methodological quality of individual studies.

6 Conclusion

Research applying artificial intelligence to autoimmune neurological disorders has grown rapidly over the past decade but is heavily concentrated on multiple sclerosis and on MRI, and remains overwhelmingly unimodal. Rarer disorders, electrophysiological, fluid-biomarker and genomic data, and genuine multimodal integration are markedly under-explored. Directing future work toward these gaps — supported by multi-

centre collaboration and responsible-AI practice — represents the clearest opportunity to make AI clinically useful across the full range of autoimmune neurological disease.

Declarations

Funding. None.

Competing interests. The author declares no competing interests.

Ethics approval. Not required (published bibliographic metadata only).

Data availability. The PubMed search export and the parsed dataset supporting this analysis will be deposited in the OSF repository accompanying the preprint and are available from the author on request.

Use of AI tools. Bibliographic records were parsed and analysed using custom Python scripts. A large-language-model assistant was used to support code development and manuscript drafting. The author reviewed and verified all content, including every reference, and is solely responsible for the work. No AI system is listed as an author, consistent with ICMJE recommendations.

Author contributions. N.K. conceived the study, designed and executed the search, analysed the data, and wrote the manuscript (sole author).

Appendix. Full PubMed search string

("multiple sclerosis"[tiab] OR "neuromyelitis optica"[tiab] OR NMOSD[tiab] OR MOGAD[tiab] OR "MOG antibody"[tiab] OR "autoimmune encephalitis"[tiab] OR "autoimmune epilepsy"[tiab] OR "paraneoplastic neurological"[tiab]) AND ("artificial intelligence"[tiab] OR "machine learning"[tiab] OR "deep learning"[tiab] OR "neural network"[tiab] OR "neural networks"[tiab] OR radiomics[tiab] OR convolutional[tiab] OR "natural language processing"[tiab] OR "data fusion"[tiab]). Limits: 2015–2026.

References

Reference list. Methods references [13–15] were verified via Crossref; corpus references [1–12, 16–21] are drawn from the analysed PubMed export and carry PMIDs. Further references may be added during revision.

1. Yousef H, Malagurski Tortei B, Castiglione F. Predicting multiple sclerosis disease progression and outcomes with machine learning and MRI-based biomarkers: a review. J Neurol. 2024. doi:10.1007/s00415-024-12651-3. PMID 39266777.

2. Voigtlaender S, Pawelczyk J, Geiger M, et al. Artificial intelligence in neurology: opportunities, challenges, and policy implications. J Neurol. 2024. doi:10.1007/s00415-024-12220-8. PMID 38367046.

3. Amin M, Martínez-Heras E, Ontaneda D, Prados Carrasco F. Artificial intelligence and multiple sclerosis. Curr Neurol Neurosci Rep. 2024;24(8):233–243. doi:10.1007/s11910-024-01354-x. PMID 38940994.

4. Talbott JF. Deep learning and the OPERA trials for multiple sclerosis. Radiology. 2022;302(3):674–675. doi:10.1148/radiol.212733. PMID 34904878.

5. Liu Y, et al. Radiomics in multiple sclerosis and neuromyelitis optica spectrum disorder. Eur Radiol. 2019. doi:10.1007/s00330-019-06026-w. PMID 30770971.

6. Meng M, et al. Independent and reproducible hippocampal radiomics biomarkers for multisite multiple sclerosis and neuromyelitis optica spectrum disorders. Mult Scler Relat Disord. 2024. doi:10.1016/j.msard.2023.105146. PMID 38007962.

7. Drenthen GS, et al. Editorial for "Deep learning-enabled identification of autoimmune encephalitis on 3D multi-sequence MRI". J Magn Reson Imaging. 2022. doi:10.1002/jmri.27951. PMID 34668607.

8. Mouazen B, et al. Machine learning and clinical EEG data for multiple sclerosis: a systematic review. Artif Intell Med. 2025. doi:10.1016/j.artmed.2025.103116. PMID 40334524.

9. Arnal Segura M, et al. Machine learning methods for classifying multiple sclerosis and Alzheimer's disease using genomic data. Int J Mol Sci. 2025;26(5):2085. doi:10.3390/ijms26052085. PMID 40076709.

10. Zhang K, et al. Predicting multiple sclerosis severity with multimodal deep neural networks. BMC Med Inform Decis Mak. 2023;23:255. doi:10.1186/s12911-023-02354-6. PMID 37946182.

11. Arrambide G, et al. Big data and artificial intelligence applied to blood and CSF fluid biomarkers in multiple sclerosis. Front Immunol. 2024;15:1459502. doi:10.3389/fimmu.2024.1459502. PMID 39493759.

12. Ning L, Wang B. Neurofilament light chain in blood as a diagnostic and predictive biomarker for multiple sclerosis: a systematic review and meta-analysis. PLoS One. 2022;17(9):e0274565. doi:10.1371/journal.pone.0274565.

13. Aria M, Cuccurullo C. bibliometrix: an R-tool for comprehensive science mapping analysis. J Informetr. 2017;11(4):959–975. doi:10.1016/j.joi.2017.08.007.

14. van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010;84(2):523–538. doi:10.1007/s11192-009-0146-3.

15. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71.

16. Seok JM, et al. Differentiation between multiple sclerosis and neuromyelitis optica spectrum disorder using a deep learning model. Sci Rep. 2023. doi:10.1038/s41598-023-38271-x. PMID 37468553.

17. Xiang Y, et al. Clinical variables, deep learning and radiomics features help predict the prognosis of adult anti-N-methyl-D-aspartate receptor encephalitis early: a two-center study in Southwest China. Front Immunol. 2022. doi:10.3389/fimmu.2022.913703. PMID 35720336.

18. Lefkovitz I, et al. Direct clinical applications of natural language processing in common neurological disorders: scoping review. JMIR Neurotechnol. 2024. doi:10.2196/51822. PMID 41341247.

19. Werthen-Brabants L, et al. The role of trustworthy and reliable AI for multiple sclerosis. Front Digit Health. 2025. doi:10.3389/fdgth.2025.1507159. PMID 40196398.

20. Campanioni S, et al. Explainable machine learning on baseline MRI predicts multiple sclerosis trajectory descriptors. PLoS One. 2024. doi:10.1371/journal.pone.0306999. PMID 39012871.

21. Kamraoui RA, et al. DeepLesionBrain: towards a broader deep-learning generalization for multiple sclerosis lesion segmentation. Med Image Anal. 2022. doi:10.1016/j.media.2021.102312. PMID 34894571.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- datasetAIautoimmuneneurology.csv
- READMEdataset.pdf