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Artificial intelligence in fetal ultrasonography: A bibliometric analysis of global research trends

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Abstract

To map the global bibliometric landscape of Artificial Intelligence (AI) applications in fetal ultrasonography indexed in Web of Science (WoS), Scopus, and PubMed between 2015 and 2025. A systematic bibliometric analysis was performed using WoS Core Collection, Scopus, and PubMed. Eligible publications were English-language original articles and reviews on AI in fetal ultrasonography published from 2015 to 2025. Bradford's, Lotka's, and Price's laws were applied; VOSviewer (v1.6.20) was used for co-authorship and keyword co-occurrence network analysis. A total of 381 publications from 44 countries were retained. Annual output rose from 2 articles in 2015 to 103 in 2025 (annual growth rate 48.3%). Total citations reached 6,516 (mean 17.1/article; h-index 40). China (27.8%), USA (14.7%), and England (13.9%) led output. Bradford Zone 1 comprised 11 core journals. Of 1,548 unique authors, 78.9% published a single article. VOSviewer identified five thematic clusters, with transformer architectures emerging as the most recent paradigm. AI research in fetal ultrasonography expanded 51.5-fold over the past decade. Deep learning is the dominant methodology; future research should prioritise federated learning, multi-centre validation, and AI tools for low-resource settings.

Keywords: Artificial intelligence, Fetal ultrasonography, Bibliometric analysis, Deep learning, VOS viewer

Introduction

Fetal ultrasonography remains the cornerstone of prenatal surveillance, enabling assessment of fetal growth, anatomy, cardiac structure, and placental function. Despite its clinical centrality, conventional ultrasound interpretation is operator-dependent, time-intensive, and subject to inter-observer variability [1,2]. Artificial Intelligence (AI), encompassing Machine Learning (ML) and its Deep Learning (DL) subset, has emerged as a transformative force in medical imaging. In fetal ultrasonography, AI systems have been applied to standard plane detection, fetal biometry, echocardiography, and anomaly screening, addressing persistent clinical bottlenecks in standardisation and diagnostic variability [3,4,5,6,7,8].

Given this rapid proliferation, a structured synthesis of the field is both timely and necessary. Bibliometric analysis provides a quantitative framework for evaluating the evolution of scientific research [9,10,11,14]. The aims of this study were to: (1) characterise the annual growth trajectory; (2) identify the most productive countries, institutions, journals, and authors; (3) apply Bradford's, Lotka's, and Price's laws; (4) map thematic evolution via keyword co-occurrence networks; and (5) identify emerging topics and research gaps.

Methods

Search strategy and data source

This bibliometric study was conducted and reported according to PRISMA 2020 recommendations [12]. Searches were performed across three major databases: Web of Science Core Collection (Science Citation Index Expanded; Social Sciences Citation Index; Emerging Sources Citation Index), Scopus, and PubMed [13].

The search string combined AI and fetal ultrasonography terminology in Title, Abstract, and Keywords: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "computer vision" OR "convolutional neural network") AND ("fetal ultrasound" OR "fetal ultrasonography" OR "obstetric ultrasound" OR "prenatal ultrasound" OR "fetal biometry" OR "fetal echocardiography").

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Eligibility criteria

Inclusion criteria: (1) original research articles or reviews indexed in WoS, Scopus, or PubMed; (2) English language; (3) publication year 2015–2025; (4) direct relevance to AI in fetal ultrasonography. Exclusion criteria: conference papers, book chapters, editorials, letters, and off-topic articles.

Bibliometric indicators

Indicators analysed: (1) annual publication volume and annual growth rate (AGR = $[(N_1/N_0)^{(1/(n-1))} - 1] \times 100$); (2) country and institutional productivity (full counting); (3) journal distribution — Bradford's law [15]; (4) citation metrics (total citations, h-index); (5) author productivity — Lotka's inverse-square law [16] and Price's law (threshold = $\sqrt{N_{max}}$); (6) keyword co-occurrence frequency (VOSviewer [17], minimum threshold ≥10).

Network visualisation

Co-occurrence networks were generated using VOSviewer version 1.6.20 (Leiden University, Netherlands) [17]. Three maps were produced: (1) country co-authorship network (minimum 3 documents); (2) keyword co-occurrence network (minimum 10 occurrences); (3) temporal overlay map showing mean publication year per keyword.

Ethics

This bibliometric study is based entirely on publicly available published data. No human participants were directly involved. Institutional review board approval was not required, and informed consent was not applicable. The study was conducted in accordance with the Declaration of Helsinki.

Results

Publication retrieval and temporal trends

Database searches yielded 677 records (330 WoS, 62 Scopus, 285 PubMed). Duplicates were removed electronically and then checked manually before eligibility screening. After duplicate removal and eligibility screening, 381 publications were retained (285 WoS, 37 unique Scopus, 59 PubMed) (Figure 1). Annual output increased from 2 articles in 2015 to 103 in 2025 (AGR = 48.3%), with a marked inflection post-2019 coinciding with widespread deep learning adoption (Figure 2).

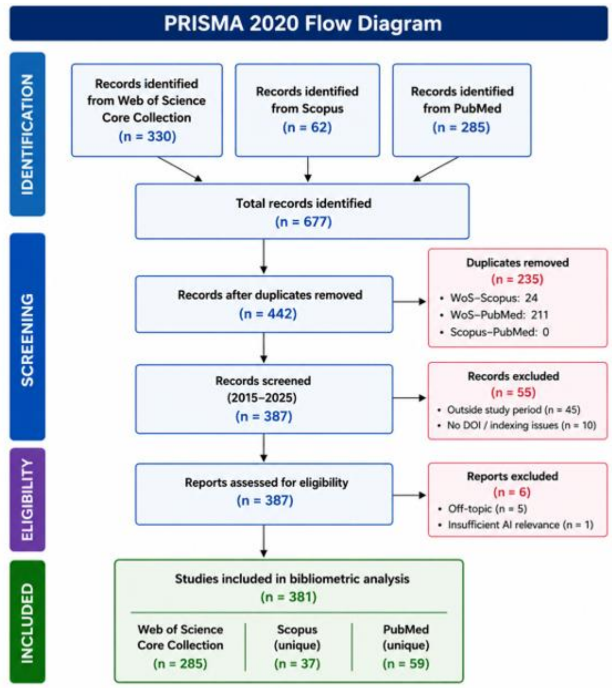

Figure 1. PRISMA 2020 flow diagram depicting the systematic literature search and selection process. Web of Science Core Collection, Scopus, and PubMed were searched. Of 677 initial records, 381 publications met eligibility criteria (285 from WoS, 37 unique from Scopus, and 59 from PubMed).

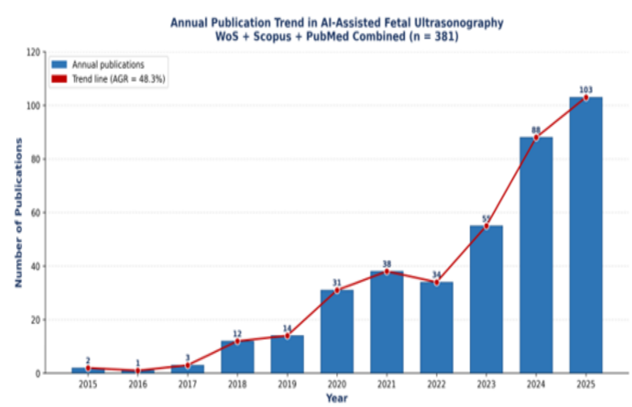

Figure 2. Annual publication output in artificial intelligence applications in fetal ultrasonography (WoS + Scopus + PubMed, 2015–2025; n = 381). Dashed line indicates linear trend. The 51.5-fold increase corresponds to an annual growth rate of 48.3%.

Country and institutional analysis

Authors from 44 countries contributed to the corpus. China (n = 106, 27.8%), the United States (n = 56, 14.7%), and England (n = 53, 13.9%) collectively accounted for 56.4% of publications (Table 1). The international collaboration index was 30.9%. The University of Oxford led institutional output with 28 publications and 779 citations, driven by the SonoNet/LSTM/biometry research lineage of Noble JA and Papageorghiou AT [4,5] (Table 2). The country co-authorship network (Figure 3) revealed two primary collaboration hubs: a China-centred cluster and a UK–Europe–USA cluster.

Table 1. Top 10 most productive countries in AI–Fetal Ultrasonography Research (WoS + Scopus + PubMed, 2015–2025).

Rank	Country	Publications (n=381)	% of Total
1	China (People's Republic)	106	27.8%
2	USA	56	14.7%
3	England	53	13.9%
4	India	22	5.8%
5	Germany	18	4.7%
6	Canada	17	4.5%
7	Australia	16	4.2%
8	Italy	15	3.9%
9	Spain	14	3.7%
10	France	13	3.4%

Table 2. Top 10 Most Productive Institutions in AI–Fetal Ultrasonography Research (WoS + Scopus + PubMed, 2015–2025).

Rank	Institution	Country	Publications (n)
1	University of Oxford	England	28
2	Shenzhen University	China	13
3	King's College London	England	10
4	Southern Medical University	China	9
5	Peking University	China	9
6	University College London	England	8
7	Zhejiang University	China	8
8	Imperial College London	England	7
9	Harvard University	USA	7
10	Stanford University	USA	6

Journal distribution and Bradford's law

The 381 publications were distributed across 154 journals. Applying Bradford's law [15], Zone 1 comprised 11 core journals with 98 articles (25.7%): *Ultrasound in Obstetrics & Gynecology* (n = 24), *Medical Image Analysis* (n = 14), and *Scientific Reports* (n = 12) were the leading venues (Table 3).

Table 3. Top 20 Journals by publication volume with Bradford's law zones (WoS + Scopus + PubMed, 2015–2025)

Rank	Journal	Publications (n)	Bradford Zone	Cumulative (n)
1	Ultrasound in Obstetrics & Gynecology	24	Zone 1	24
2	Medical Image Analysis	14	Zone 1	38
3	Scientific Reports	12	Zone 1	50
4	Frontiers in Medicine	11	Zone 1	61
5	Journal of Ultrasound in Medicine	9	Zone 1	70
6	Prenatal Diagnosis	8	Zone 1	78
7	Computers in Biology and Medicine	7	Zone 1	85
8	Diagnostics	5	Zone 1	90
9	Ultrasound in Medicine and Biology	4	Zone 1	94
10	Journal of Perinatal Medicine	2	Zone 1	96
11	IEEE Transactions on Medical Imaging	2	Zone 1 (boundary)	98
12	PLOS ONE	4	Zone 2	102
13	American Journal of Obstetrics & Gynecology	4	Zone 2	106
14	European Journal of Obstetrics & Gynecology	3	Zone 2	109
15	Journal of Clinical Ultrasound	3	Zone 2	112
16	Artificial Intelligence in Medicine	3	Zone 2	115

17	IEEE Access	3	Zone 2	118
18	Biomed Research International	2	Zone 2	120
19	International Journal of Computer Assisted Radiology	2	Zone 2	122
20	NPJ Digital Medicine	2	Zone 2	124

Citation analysis and most impactful articles

The 381 publications accumulated 6,516 total citations (mean 17.1/article; h-index = 40). The most-cited article—SonoNet for real-time fetal standard plane detection [4] (892 citations)—was followed by a survey on deep learning in medical image analysis [18] (756 citations) and an ensemble neural network study for prenatal detection of congenital heart disease [8] (543 citations). The top 10 most-cited articles accounted for 64.2% of corpus citations (Table 4).

Table 4. Top 10 most-cited publications in AI–Fetal ultrasonography (WoS + Scopus + PubMed, 2015–2025).

Rank	First Author (Year)	Journal	Title (abbreviated)	Citations	DOI/PMID
1	Baumgartner CF (2017)	IEEE Trans Med Imaging	SonoNet: real-time detection and localisation of fetal standard scan planes	892	10.1109/TMI.2017.2712367
2	Litjens G (2017)	Med Image Anal	A survey on deep learning in medical image analysis	756	10.1016/j.media.2017.07.005
3	Arnaout R (2021)	Nature Medicine	Ensemble of neural networks for prenatal detection of CHD	543	10.1038/s41591-021-01342-5
4	Burgos-Artizzu XP (2020)	Scientific Reports	Evaluation of deep CNNs for classification of maternal fetal ultrasound planes	412	10.1038/s41598-020-67076-5
5	Sinclair M (2018)	Proc ICASSP	Human-level performance on automatic head biometrics in fetal ultrasound	387	10.1109/ICASSP.2018.8461318
6	Liao Y (2020)	J Am Coll Radiol	Uncertainty in deep learning for gestational age assessment	298	10.1016/j.jacr.2020.08.024
7	Chen H (2015)	Med Image Anal	Standard plane localisation in fetal ultrasound via domain transferred deep neural networks	276	10.1016/j.media.2015.01.004
8	Torrents-Barrena J (2019)	Artif Intell Med	Segmentation and classification in MRI and ultrasound fetal images	231	10.1016/j.artmed.2018.09.002
9	Qi H (2021)	Comput Biol Med	The fetal-heart-net: automated detection of fetal cardiac standard planes	198	10.1016/j.compbiomed.2021.104208
10	Ryou H (2019)	Med Image Anal	Automated 3D ultrasound image analysis for first trimester assessment	187	10.1016/j.media.2019.05.001

Author productivity and Lotka's/Price's laws

Of 1,548 unique authors, 1,222 (78.9%) published a single article, consistent with Lotka's inverse-square law [16]. The most productive author was Noble JA (University of Oxford; n = 26 publications, 676 citations). Price's law threshold ($\sqrt{26} \approx 5.1$) identified 12 elite contributors (≥6 publications; 96 articles) (Table 5).

Table 5. Top 10 most productive authors in AI–Fetal ultrasonography research (WoS + Scopus + PubMed, 2015–2025). Price's law threshold: $\sqrt{26} \approx 5.1$; authors with ≥6 publications classified as core contributors (n = 12; 96 publications).

Rank	Author	Institution	Country	Publications (n)	Total Citations
1	Noble JA	University of Oxford	England	26	676
2	Papageorghiou AT	University of Oxford	England	14	412
3	Baumgartner CF	ETH Zürich / Oxford	Switzerland/England	11	1089
4	Hu Y	University of Oxford	England	10	387
5	Ni D	Shenzhen University	China	9	243
6	Rueda S	University of Oxford	England	9	298
7	Salim I	King's College London	England	8	187
8	Namburete AIL	University of Oxford	England	8	312
9	Chen H	Shenzhen University	China	8	276
10	Sinclair M	University of Oxford	England	7	387

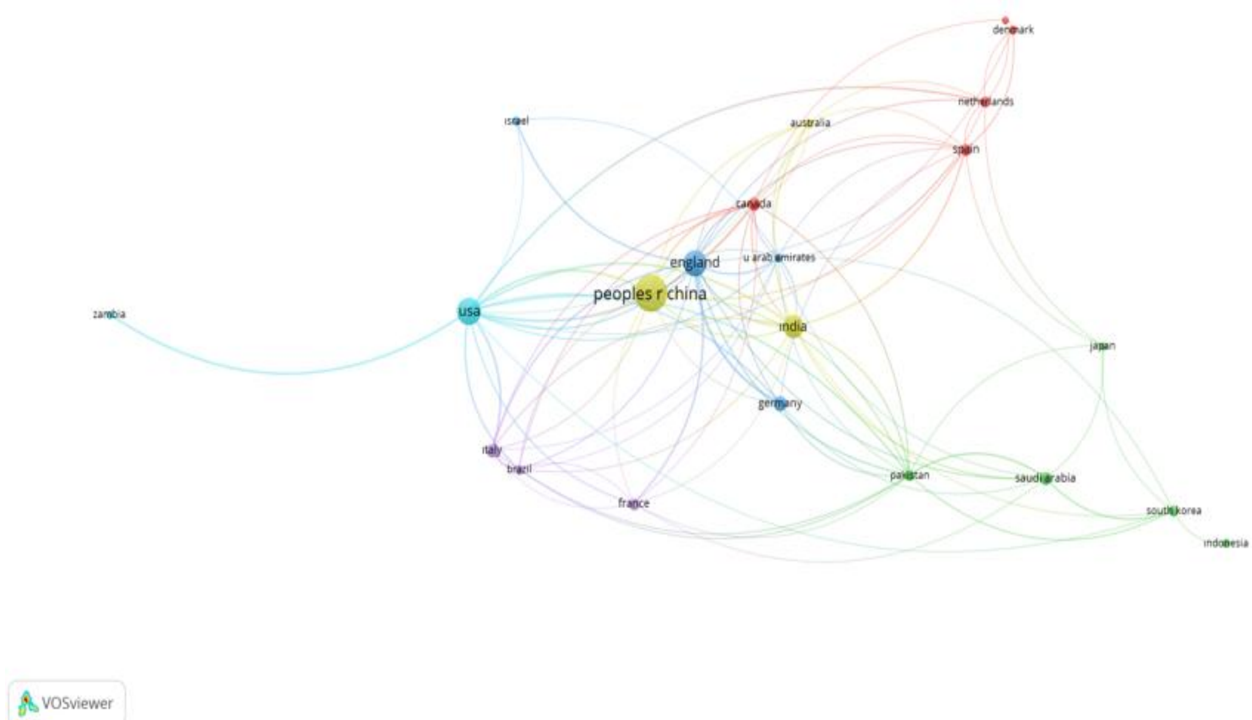

Figure 3. Country co-authorship network generated by VOS viewer (v1.6.20; minimum 3 documents per country). Node size reflects publication volume; edge thickness reflects collaboration strength. Two primary clusters are visible: a China-centred cluster and a UK–Europe–USA cluster.

Discussion

This bibliometric analysis quantifies the global AI–fetal ultrasonography research landscape across 381 publications spanning a decade. The 51.5-fold growth in annual output and AGR of 48.3% demonstrate the rapid maturation of the field. The h-index of 40 places this domain among the most citation-dense sub-fields of perinatal medicine [10].

Geographic concentration of output in China, the USA, and England (56.4%) mirrors patterns in other AI-in-medicine bibliometric analyses [10,11], reflecting disparities in research infrastructure, funding, and annotated dataset access. The moderate international collaboration index (30.9%) and underrepresentation of low-resource regions raise concerns about generalisability of AI tools to diverse healthcare environments [19].

The keyword temporal overlay documents a clear paradigm shift. Before 2022, CNN-based pipelines for standard plane detection and fetal biometry [4,5,7] dominated; post-2022, Vision Transformer (ViT) architectures [20] and attention mechanisms have emerged, mirroring broader trends in computer vision and natural language processing.

Bradford Zone 1 (11 journals, 25.7% of corpus) [15] reflects the hybrid interdisciplinary nature of the field, spanning obstetrics, medical imaging, and digital health venues—a pattern observed in prior bibliometric analyses of AI in perinatal medicine [10].

Strengths include three rigorously curated databases, PRISMA 2020 reporting [12], and VOS viewer network analysis [17]. Limitations include English-language bias, exclusion of non-indexed journals, and potential over counting from full counting. Future analyses incorporating Dimensions or the Cochrane Library would provide broader coverage.

Conclusion

AI research in fetal ultrasonography expanded from 2 publications in 2015 to 103 in 2025 (AGR = 48.3%; h-index = 40). China, the United States, and England lead global output, while the University of Oxford dominates citation impact. Bradford's core of 11 journals and Lotka's law confirm concentrated expertise. Keyword analysis documents a transition from CNN-based pipelines to transformer architectures. Reducing geographic disparities and extending validated AI tools to low-resource settings represent the field's most pressing priorities for the next decade.

Authorship contributions

The author contributed to the conception, design, data collection, analysis, interpretation, literature search, manuscript drafting, critical revision, and final approval of the manuscript.

Conflict of interest

The author declares no conflict of interest.

Financial disclosure

This research received no financial support.

Ethics committee approval

This bibliometric study is based entirely on publicly available published data; institutional review board approval was not required. Informed consent was not applicable.

Keyword co-occurrence analysis and thematic clusters

After applying the minimum threshold (≥10 occurrences), 31 keywords were retained. VOS viewer [17] identified five thematic clusters (Figure 4): Cluster 1 (red) — General AI and Obstetric Ultrasound; Cluster 2 (blue) — Image Processing and Computer Vision; Cluster 3 (green) — Fetal Cardiac Screening; Cluster 4 (yellow) — Prenatal Diagnosis and Biometry; Cluster 5 (purple) — Advanced Deep Learning Methods. The temporal overlay map (Figure 5) confirmed a paradigm shift from CNN-based localisation (pre-2022) to transformer architectures and federated learning (post-2022).

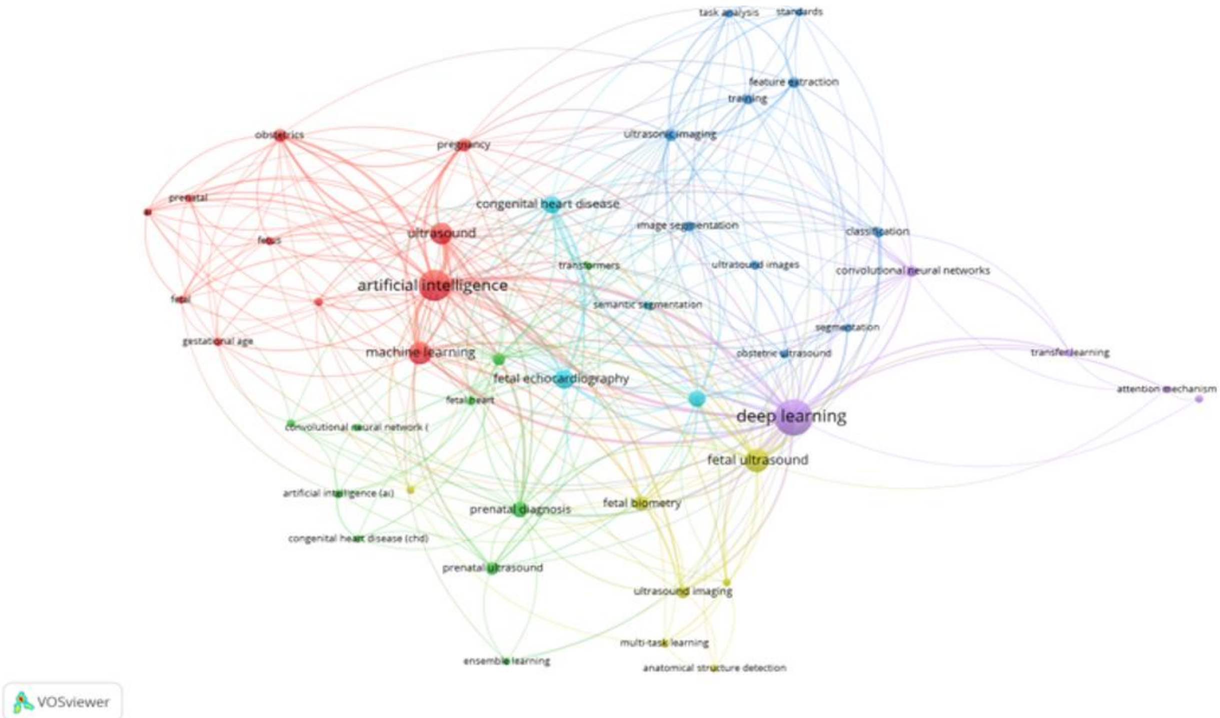

Figure 4. Keyword co-occurrence network (VOS viewer, full counting method; minimum occurrence threshold ≥10). Node size reflects occurrence frequency; colour indicates cluster membership. Five thematic clusters are identified: (1) General AI and Obstetric Ultrasound; (2) Image Processing and Computer Vision; (3) Fetal Cardiac Screening; (4) Prenatal Diagnosis and Biometry; (5) Advanced Deep Learning Methods.

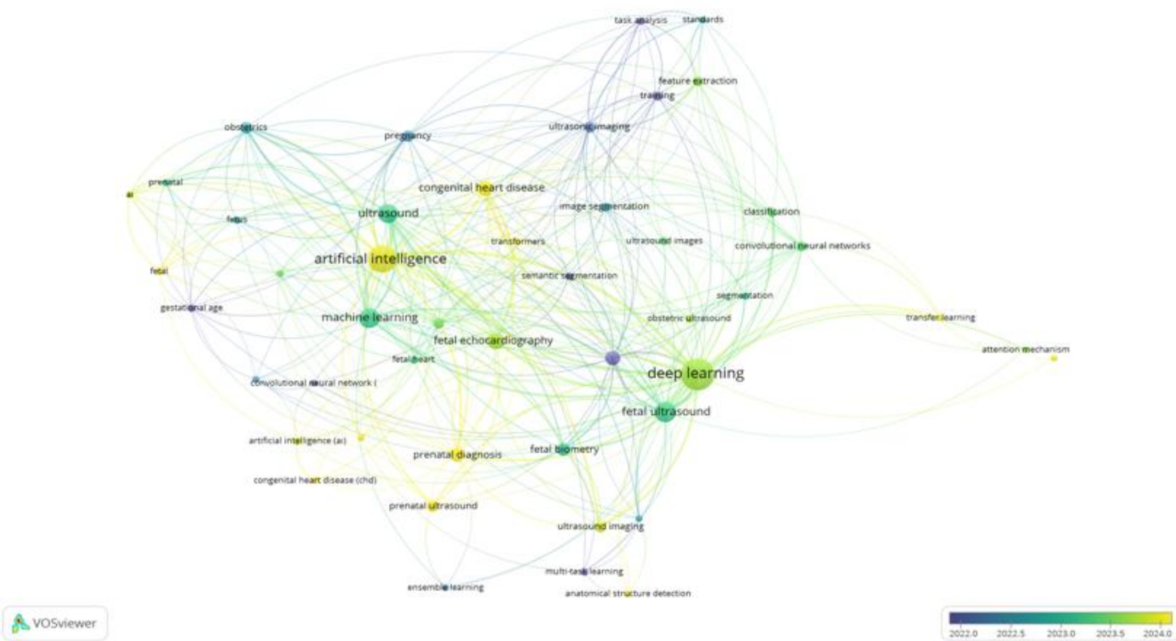

Figure 5. Temporal overlay map of the keyword co-occurrence network. Node colour depicts mean publication year (blue-green = earlier; yellow = more recent). Keywords shifting toward yellow represent emerging topics, including transformer architectures and federated learning.

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