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REVIEW ARTICLE

Harmonizing Tradition, Algorithm, and Innovation: A Bibliometric Study on AI in Traditional Music

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ABSTRACT

This study aims to explore the intersection of artificial intelligence (AI) and traditional music through a bibliometric lens, identifying key trends, contributors, and research hotspots within this emerging interdisciplinary field. The bibliometric data were extracted from the Scopus database, which covers publications from 1974 to April 19, 2025, using keywords related to AI and traditional music. This study utilized BiblioMagika to analyze publication trends, prolific authors, contributing countries, source titles, keyword co-occurrence patterns, and collaboration networks. The results indicate a significant increase in research output on the intersection of artificial intelligence and traditional music since 2019. Over time, the thematic focus has evolved from early applications such as signal processing, genre classification, and feature extraction rooted in music information retrieval, to more sophisticated areas including generative AI composition, cultural modeling of indigenous musical forms, and multimodal human-AI interaction in performance and education contexts.

Contribution/Originality: This study provides scholars, educators, and digital heritage practitioners with an overview of the intellectual structure and evolution of AI applications in traditional music. This study represents one of the first systematic bibliometric analyses at the intersection of AI and traditional music. It suggests future directions in leveraging AI for cultural heritage research.

1. Introduction

In recent decades, the rapid advancement of artificial intelligence (AI) has significantly reshaped the landscape of music research, enabling new possibilities in composition, analysis, retrieval, and preservation. AI technologies such as deep learning, generative adversarial networks (GANs), and symbolic modeling have evolved from rule-based systems to architectures like recurrent neural networks (RNNs), transformers, and

Convolutional neural networks (CNNs), capable of generating stylistically coherent music and performing complex recognition tasks such as genre classification, emotion detection, and automatic transcription (Herremans et al., 2017; Briot et al., 2020). The field of music education has also benefited from AI, with personalized learning platforms and intelligent tutoring systems becoming increasingly prevalent (Merchán Sánchez-Jara et al., 2024; Xambó & Roma, 2024).

At the same time, traditional music has garnered increasing attention in the domains of digital humanities and computational ethnomusicology, particularly as scholars seek to preserve intangible cultural heritage and understand the diversity of musical practices through algorithmic and data-driven approaches. For example, Tahvanainen et al. (2024) compared audio features of Finnish folk instrument recordings to support automated classification, while Kramer (2024) explored how Alan Lomax's Global Jukebox project merged ethnomusicology and computational tools to promote cultural equity. Deep learning approaches have further enabled symbolic modeling and emotion-based analysis of traditional music performances (Nagaraj et al., 2024). In addition, Bryan-Kinns et al. (2024) demonstrated how genre incongruity in AI-assisted music creation can inspire cultural reflection and user engagement. These interdisciplinary studies illustrate how artificial intelligence and computational frameworks can support the transcription, interpretation, and revitalization of regional music traditions.

Bridging these two trajectories, an emerging body of interdisciplinary research has begun to explore the intersection of AI and traditional music. Early works in this space employed signal processing techniques such as hidden Markov models (HMM) and dynamic time warping (DTW), while recent studies have incorporated generative models, multimodal datasets, and culturally adaptive algorithms for tasks like music style transfer, ritual performance analysis, and regional opera modeling (Juhász, 2015; Y. Li et al., 2023). However, this body of work remains fragmented, often limited to case-based or regional studies; bibliometric research specifically focused on the intersection between AI and traditional or folk music is still limited.

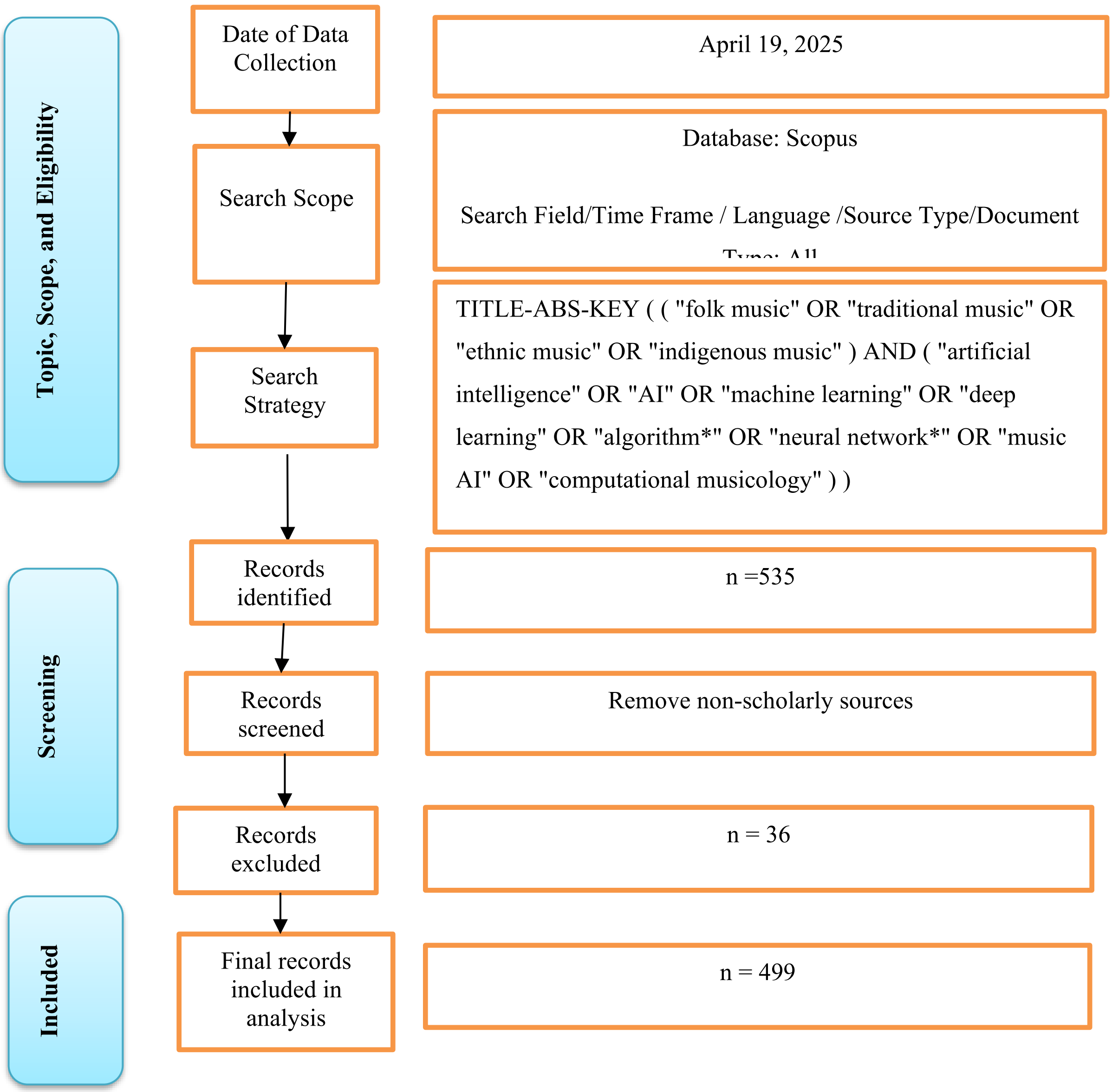
This study aims to conduct a systematic bibliometric analysis of research literature in the field of artificial intelligence and music included in the Scopus database. This study aims to expand the depth and breadth of existing research on artificial intelligence and music, identify key academic contributors, reveal cutting-edge research topics, and provide strategic guidance for future research. The analysis covers the evolution trend of relevant publications, the scientific research output of authors, institutions, countries and journals, the identification of highly cited literature, and the co-occurrence network and overlay visualization map constructed based on author keywords. This study focuses on the following three core research questions:

i. Who are the key authors, institutions, and journals in the domain of AI and traditional music?
ii. What are the key themes and keywords in artificial intelligence and music research?
iii. What are the current emerging research directions and future development potential?

2. Methods

This study focuses on the intersection between artificial intelligence (AI) and traditional music, encompassing research that explores technological applications in traditional music practices across global contexts. Scopus was chosen for data collection due to its broad subject coverage, academic reliability, and compatibility with bibliometric tools such as biblioMagika (Echchakoui, 2020; Singh et al., 2021). Bibliographic data were collected from the Scopus database on April 19, 2025. The search was conducted within the title, abstract, and keyword fields using a Boolean query designed to capture research at the intersection of artificial intelligence and traditional music. Specifically, the following search expression was employed: TITLE-ABS-KEY (("folk music" OR "traditional music" OR "ethnic music" OR "indigenous music") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "algorithm*" OR "neural network*" OR "music AI" OR "computational musicology")). A total of 535 documents were initially retrieved, comprising journal articles and conference papers. A round of data cleaning was performed to exclude non-scholarly formats such as book chapters, editorials, and retracted publications. After removing duplicates and irrelevant records, 499 documents met the thematic inclusion criteria and were retained for bibliometric analysis. Figure 1 illustrates the procedure employed for the retrieval and screening of publications relevant to this study.

Figure 1: Flow diagram of search strategy



Source: Author adapted from Alam et al. (2023)

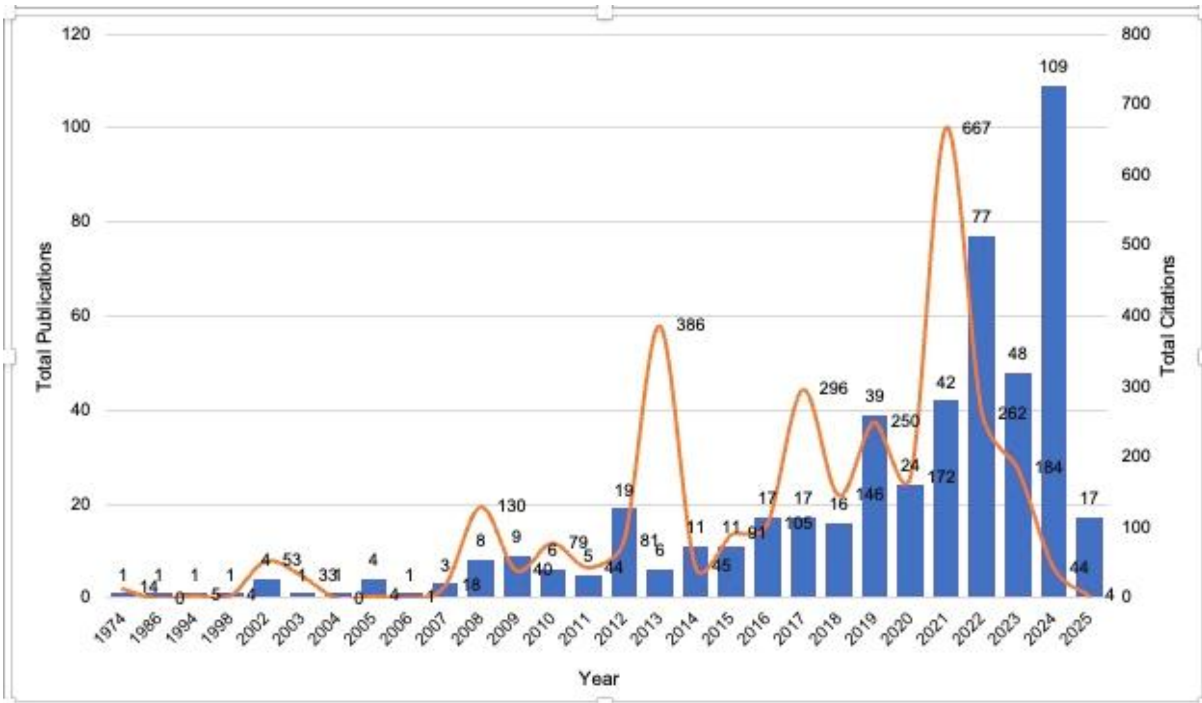
This study employed BiblioMagika, a user-friendly bibliometric analysis tool developed based on the Bibliometrix R package (Aria & Cuccurullo, 2017), in conjunction with OpenRefine for data cleaning and harmonization. BiblioMagika facilitates the generation of descriptive statistics such as annual publication trends, citation frequencies, country collaboration networks, and source journal distributions. These functions enable a comprehensive examination of research productivity, knowledge diffusion pathways, and the intellectual structure of the field (Aria & Cuccurullo, 2017; Huang et al., 2022). OpenRefine was used to clean and normalize author names, institutional affiliations, and keywords, ensuring consistency in data integration prior to visualization and analysis.

3. Results

3.1. Annual Scientific Production

Figure 2 shows the annual publication and citation data for the intersection of AI and traditional music from 1974 to April 2025. In the early stage (1974 to 2007), the number of publications ranged from 1 to 4 per year. However, the four publications in 2002 had 53 citations, indicating that influential early works began to emerge. The period from 2008 to 2012 shows a gradual increase in publications, from 8 in 2008 to 19 in 2012, while there was a relatively stable period with 11 to 17 publications per year from 2013 to 2018. The period from 2019 to 2025 enters a rapid expansion phase. The number of publications reaches its highest point in 2024, with 109.

Figure 2: Publication trends and growth phases from 1974–2025



Sources: Author's own work

Table 1 lists the bibliometric indicators for the period from 1974 to 2025, including total number of publications (TP) 499, total number of citations (TC) 3158, average number of citations per paper (C/P) 6.33 and impact index (h-index 27, g-index 44, m-index 0.519). 2021 was the most influential year, with 42 publications receiving a total of 667 citations, setting the highest h-index (12), g-index (25) and m-index (2.4). In addition, 2013 also showed extraordinary influence, with only 6 papers receiving a total of 386 citations, and a C/P of 64.33, the highest citation rate for a single paper.

Table 1: Annual Research Output and Citation Metrics

Year	TP	NCA	NCP	TC	C/P	C/CP	h-index	g-index	m-index
1974	1	1	1	14	14.00	14.00	1	1	0.019
1986	1	2	0	0	0.00	0.00	0	0	0.000
1994	1	4	1	5	5.00	5.00	1	1	0.031
1998	1	3	1	4	4.00	4.00	1	1	0.036
2002	4	12	4	53	13.25	13.25	3	4	0.125
2003	1	3	1	33	33.00	33.00	1	1	0.043
2004	1	3	0	0	0.00	0.00	0	0	0.000
2005	4	11	2	4	1.00	2.00	2	2	0.095
2006	1	3	1	1	1.00	1.00	1	1	0.050
2007	3	7	2	18	6.00	9.00	2	3	0.105
2008	8	24	7	130	16.25	18.57	6	8	0.333
2009	9	18	7	40	4.44	5.71	3	6	0.176
2010	6	21	5	79	13.17	15.80	5	6	0.313
2011	5	14	5	44	8.80	8.80	3	5	0.200
2012	19	57	15	81	4.26	5.40	6	8	0.429
2013	6	19	5	386	64.33	77.20	2	6	0.154
2014	11	32	9	45	4.09	5.00	3	6	0.250
2015	11	33	10	91	8.27	9.10	4	9	0.364
2016	17	54	15	105	6.18	7.00	5	9	0.500
2017	17	71	16	296	17.41	18.50	9	17	1.000
2018	16	56	15	146	9.13	9.73	7	11	0.875
2019	39	143	28	250	6.41	8.93	9	14	1.286
2020	24	68	19	172	7.17	9.05	7	12	1.167
2021	42	111	37	667	15.88	18.03	12	25	2.400
2022	77	169	51	262	3.40	5.14	8	12	2.000
2023	48	121	26	184	3.83	7.08	8	12	2.667
2024	109	245	28	44	0.40	1.57	3	3	1.500
2025	17	58	2	4	0.24	2.00	1	2	1.000
Total	499	1363	313	3158	6.33	10.09	27	44	0.519

Notes: TP (Total Publications), NCA (Number of Cited Articles), NCP (Number of Citing Papers), TC (Total Citations), C/P (Citations per Paper), C/CP (Citations per Citing Paper).

Sources: Author's own work

3.2. Source Analysis

Out of the 499 publications, journals account for 279 records (55.91%), followed by conference proceedings (184 records, 36.87%) and book series (36 records, 7.21%). Among them, the largest number of publications were in English (467 articles, 93.59%), followed by Chinese (30 articles, 6.01%), and only 1 article each in other languages such as French, Italian, and Russian (0.20%).

Most of the research belongs to computer science (382, 76.55%) and engineering (239, 47.90%), followed by mathematics (147, 29.46%). Other related disciplines include physics and astronomy (9.42%), arts and humanities (9.02%), and decision sciences (7.41%). A small number of publications involve fields such as social sciences, medicine, neuroscience, and psychology, reflecting the interdisciplinary nature of AI and traditional music research (Table 2).

Table 2: Publication By Subject Area

Subject Area	TP	%
Computer Science	382	76.55
Engineering	239	47.90
Mathematics	147	29.46
Physics and Astronomy	47	9.42
Arts and Humanities	45	9.02
Decision Sciences	37	7.41
Materials Science	29	5.81
Social Sciences	25	5.01
Energy	19	3.81
Medicine	16	3.21
Neuroscience	13	2.61
Chemical Engineering	10	2.00
Environmental Science	10	2.00
Psychology	7	1.40
Multidisciplinary	6	1.20
Biochemistry, Genetics and Molecular Biology	5	1.00
Business, Management and Accounting	5	1.00
Earth and Planetary Sciences	3	0.60
Chemistry	2	0.40
Economics, Econometrics and Finance	1	0.20
Health Professions	1	0.20
Nursing	1	0.20

Sources: Author‘s own work

Table 3 lists the source journals with the highest output in the fields of artificial intelligence and traditional music research. Applied Mathematics and Nonlinear Science contributed 40 publications, but its citation rate was relatively low (C/P = 0.45, h-index = 2). It was followed by Lecture Notes in Computer Science, which contributed 15 papers, and Mobile Information Systems, which contributed 12 papers, the latter of which had a relatively high citation impact (C/P = 6.08, g-index = 8).

In terms of the number of citations, the Journal of New Music Research received 152 citations for only seven papers, ranking first and having the highest average citation rate (C/P = 21.71). Wireless Communications and Mobile Computing and ICASSP Proceedings accumulated 102 and 74 citations, respectively. Despite the small number of publications, the average citation rate of each paper was high (C/P > 14).

Ranked by the H-index, which measures the performance of sustained citations, Wireless Communications and Mobile Computing and Mobile Information Systems have an H-index of 5 and 4, respectively. IEEE Access, ICASSP Proceedings, and Journal of New Music Research also perform well (≥4).

In terms of the g-index (which emphasizes highly cited publications), Mobile Information Systems has a g-index of 8, followed by Wireless Communications and Mobile Computing (g = 7) and Journal of New Music Research (g = 7).

Table 3: Most Productive Source Title

Source Title	TP	NCA	NCP	TC	C/P	C/CP	h	g	m
Applied Mathematics and Nonlinear Sciences	40	46	13	18	0.45	1.38	2	2	0.667
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	15	48	11	40	2.67	3.64	4	5	0.167
Mobile Information Systems	12	18	10	73	6.08	7.30	4	8	0.800
ACM International Conference Proceeding Series	12	30	8	39	3.25	4.88	4	6	0.211
Computational Intelligence and Neuroscience	8	9	6	26	3.25	4.33	3	4	0.600
Wireless Communications and Mobile Computing	7	10	7	102	14.57	14.57	5	7	1.000
Journal of New Music Research	7	26	6	152	21.71	25.33	4	7	0.364
IEEE Access	6	23	4	71	11.83	17.75	4	6	0.500
Applied Sciences (Switzerland)	5	20	4	16	3.20	4.00	2	4	0.286
Computer-Aided Design and Applications	5	8	1	1	0.20	1.00	1	1	0.500
ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings	5	14	4	74	14.80	18.50	4	5	0.222
Dianzi Yu Xinxi Xuebao/Journal of Electronics and Information Technology	5	15	4	13	2.60	3.25	2	3	0.105
Journal of Environmental and Public Health	5	8	3	7	1.40	2.33	2	2	0.500
Scientific Programming	4	5	3	49	12.25	16.33	2	4	0.400
Xi Tong Gong Cheng Yu Dian Zi Ji Shu/Systems Engineering and Electronics	4	16	3	10	2.50	3.33	2	3	0.095
European Signal Processing Conference	4	14	3	9	2.25	3.00	2	3	0.071
Entertainment Computing	4	10	4	9	2.25	2.25	2	2	1.000
Mathematics	4	9	4	50	12.50	12.50	3	4	0.429
Lecture Notes in Electrical Engineering	4	6	2	2	0.50	1.00	1	1	0.200
Journal of Physics: Conference Series	3	5	3	26	8.67	8.67	2	3	0.286

Notes: TP (Total Publications), NCA (Number of Cited Articles), NCP (Number of Citing Papers), TC (Total Citations), C/P (Citations per Paper), C/CP (Citations per Citing Paper).

Sources: Author‘s own work

3.3. Highly Cited Documents

Table 4 lists the 20 most cited papers in the field of AI and traditional music research. In terms of topics, the most cited articles focus on music emotion recognition (Hizlisoy et al., 2021), direction of arrival (DOA) estimation in MIMO systems (Wan et al., 2021), and deep learning models for music feature extraction and classification (Zhang K., 2021; Liu et al., 2021). In terms of methodology, most of these studies adopted convolutional neural networks (CNN), recurrent neural networks (RNN), and the MUSIC algorithm. In addition, some publications explored cultural and educational applications of AI in the field of music. For example, Macintyre et al. (2017) explored learning Gaelic through music, while Lidy et al. (2010) focused on the analysis of non-Western and ethnic minority music collections.

Table 4: Highly Cited Documents

Author(s)	Title	TC	C/Y
Reddish et al. (2013)	Let's Dance Together: Synchrony, Shared Intentionality and Cooperation	354	27.23
Hizlisoy et al. (2021)	Music emotion recognition using convolutional long short term memory deep neural networks	121	24.20
Wan et al. (2021)	DOA and Polarization Estimation for Non-Circular Signals in 3-D Millimeter Wave Polarized Massive MIMO Systems	103	20.60
Wan et al.(2017)	DOA estimation for coherently distributed sources considering circular and noncircular signals in massive MIMO systems	95	10.56
Sturm et al. (2019)	Machine learning research that matters for music creation: A case study	76	10.86
Liu et al. (2021)	DOA estimation based on CNN for underwater acoustic array	71	14.20
Macintyre et al. (2017)	Heritage Passions, Heritage Convictions, and the Rooted L2 Self: Music and Gaelic Language Learning in Cape Breton, Nova Scotia	63	7.00
Hu et al. (2021)	Multiple Source Direction of Arrival Estimations Using Relative Sound Pressure Based Music	54	10.80
Zhang K. (2021)	Music Style Classification Algorithm Based on Music Feature Extraction and Deep Neural Network	46	9.20
Lin et al. (2018)	Heterogeneous knowledge-based attentive neural networks for short-term music recommendations	45	5.63
Lidy et al. (2010)	On the suitability of state-of-the-art music information retrieval methods for analyzing, categorizing and accessing non-Western and ethnic music collections	43	2.69
Chen K. et al. (2020)	Music Sketchnet: Controllable Music Generation Via Factorized Representations of Pitch and Rhythm	41	6.83
Agarwal & Chen (2008)	Applicability of MUSIC-type imaging in two-dimensional electromagnetic inverse problems	40	2.22
Zhang J. (2021)	Music Feature Extraction and Classification Algorithm Based on Deep Learning	38	7.60
Erkut et al. (2002)	Acoustical analysis and model-based sound synthesis of the kantele	37	1.54
Xing et al. (2015)	Emotion-driven Chinese folk music-image retrieval based on DE-SVM	34	3.09
Cheng Y et al. (2020)	Convolutional neural networks approach for music genre classification	33	5.50

Lu et al. (2017)	Deep ranking: Triplet MatchNet for music metric learning	33	3.67
Pikrakis et al. (2003)	Recognition of isolated musical patterns using context dependent dynamic time warping	33	1.43

Sources: Author‘s own work

3.4. Author Analysis

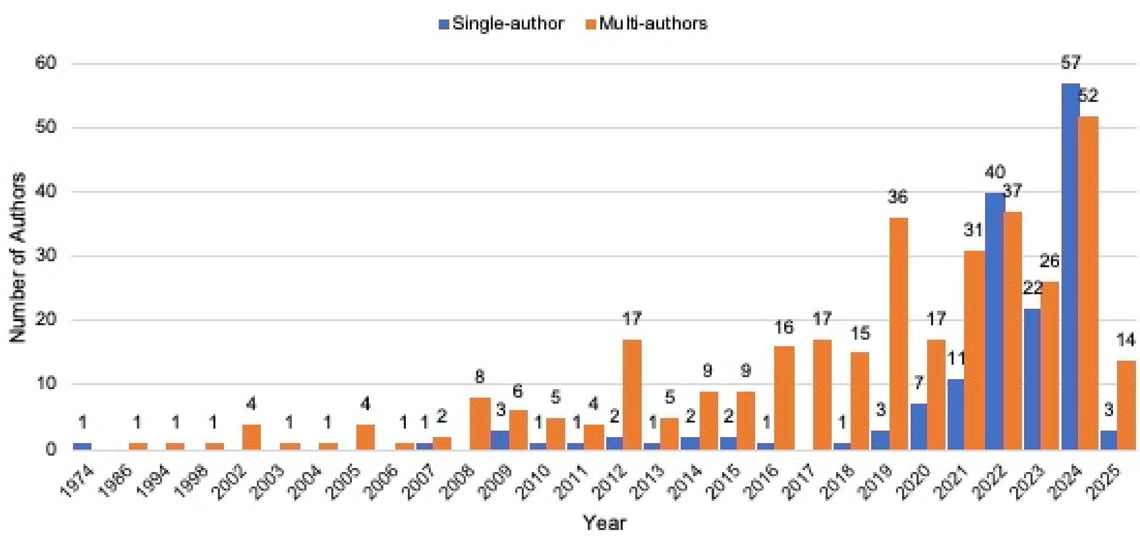
The distribution of authors follows Lotka's law; that is, most authors contribute only once, while a few authors publish multiple works. In addition, the author trend in AI and traditional music research has clearly shifted toward collaborative research. Of the 499 papers, 340 (68.14%) involved two or more authors, while 159 (31.86%) were single-authored (see Table 5). Since 2012, the number of multi-author publications has consistently exceeded that of single-author works. However, 2024 was an unusual year, with the number of single-author publications temporarily exceeding collaborative publications. These data demonstrate the teamwork and cross-disciplinary collaboration that advances the intersection of AI and musical heritage research (see Figure 3).

Table 5: Author Count Distribution per Publication

Author Count	Frequency
1	159
2	109
3	88
4	64
5	39
6	23
7	10
8	3
9	2
10	1
11	1
Grand Total	499

Sources: Author‘s own work

Figure 3: Temporal Trend in Single-Author and Multi-Author Publications



Sources: Author‘s own work

Table 6 lists the most productive and influential authors in the fields of AI and traditional music research. Juhász Zoltán (Hungary) and Pikrakis Aggelos (Greece) are the most productive scholars, with 5 papers each. Pikrakis also has high total citations (TC=51) and average citations per paper (C/P=10.2). Wan Liangtian (China) stands out as the most influential author in terms of citations, with 215 citations for just 3 papers and a high C/P of 71.67. Theodoridis Sergios and Kamarotos Dimitris (both from Greece) have a combination of high productivity (TP=4), robust average citations (C/P=11.0), and stable h- and g-index values (h=3, g=4). However, several authors from Vietnam had zero citations despite publishing multiple papers, suggesting that their contributions were either recent or their academic dissemination was limited.

Table 6: Most Productive Author

Full Name	Country	TP	TC	C/P	h-index	g-index
Juhász, Zoltán	Hungary	5	30	6.00	3	5
Pikrakis, Aggelos	Greece	5	51	10.20	4	5
Jiménez-Bravo, Diego M.	Spain	4	1	0.25	1	1
Sturm, Bob L.T.	Sweden	4	19	4.75	3	4
Marolt, Matija	Slovenia	4	33	8.25	3	4
Theodoridis, Sergios	Greece	4	44	11.00	3	4
Kamarotos, Dimitris	Greece	4	44	11.00	3	4
Navarro-Cáceres, María	Spain	3	1	0.33	1	1
Xie, Lingyun	China	3	6	2.00	1	2
Lartillot, Olivier	Norway	3	5	1.67	2	2
Zhou, Li	China	3	9	3.00	2	3
Wan, Liangtian	China	3	215	71.67	3	3
Xing, Baixi	China	3	38	12.67	2	3
Tieu, Thanh Nhat	Viet Nam	2	0	0.00	0	0
Do, Huy Quang	Viet Nam	2	0	0.00	0	0
Bui, Hung Tung	Viet Nam	2	0	0.00	0	0
Nguyen, Huy Do Nhat	Viet Nam	2	0	0.00	0	0
Wang, Chunqiu	China	2	0	0.00	0	0
Mai, Quan Anh	Viet Nam	2	0	0.00	0	0
Geng, Xucheng	China	2	0	0.00	0	0
Park, Kyu-Sik	South Korea	2	2	1.00	1	1
d'Aquin, Mathieu	France	2	1	0.50	1	1
Sales Mendes, André	Spain	2	0	0.00	0	0
Sturm, Bob L. T.	Sweden	2	1	0.50	1	1
Silva, Luís Augusto	Spain	2	0	0.00	0	0

Notes: TP (Total Publications), TC (Total Citations), C/P (Citations per Paper).

Sources: Author‘s own work

Table 7 summarizes the most productive and influential institutions in the fields of AI and traditional music research. Chinese institutions dominate in terms of total number of publications, with Tianjin University leading the field with 87 papers and an H-index of 14. Other Chinese universities, such as Shanghai Jiao Tong University, Zhejiang University, and University of Electronic Science and Technology of China, also show stable productivity and citation rates. In terms of citation impact, Queen Mary University of London (UK) and University of Athens (Greece) outperform other institutions, with an average of 14.94 and 13.33 citations per publication, respectively.

Table 7: High-impact Author Keywords in AI and Traditional Music Research

Institution	Country	TP	TC	C/P	h-index
Tianjin University	China	87	793	9.11	14
Shanghai Jiao Tong University	China	23	52	2.26	6
Queen Mary University of London	UK	16	239	14.94	7
Fpt University	Vietnam	14	0	0	0
Communication University of China	China	14	100	7.14	4
University of Electronic Science and Technology	China	14	81	5.79	4
Zhejiang University	China	14	104	7.43	4
Shaanxi Normal University	China	12	32	2.67	5
Air Force Engineering University	China	12	63	5.25	4
Universidad de Salamanca	Spain	10	4	0.4	2
University of Athens	Greece	9	120	13.33	5
Hangzhou Dianzi University	China	9	139	15.44	4

Sources: Author‘s own work

3.5. Country-Level Research Contributions

Table 8 lists the most active countries in AI and traditional music research. China contributed 789 publications, far more than any other country, and received an h-index of 31. France (C/P = 18.53) and the United Kingdom (C/P = 10.54) outperformed other countries in terms of academic impact, with higher average citations per publication. The United States, while not producing as many publications (TP = 57), ranked second in total citations (TC = 537) and had an h-index of 13. India and Indonesia are emerging contributors, but their average citations per document are lower.

Table 8: Most Productive and Influential Countries

Country	TP	TC	C/P	h-index
China	789	4987	6.32	31
United States	57	537	9.42	13
India	49	70	1.43	4
United Kingdom	37	390	10.54	14
Indonesia	35	110	3.14	9
South Korea	34	235	6.91	10
Greece	29	192	6.62	7
Spain	28	212	7.57	10
France	17	315	18.53	5
Sweden	16	120	7.5	5
Vietnam	14	0	0	0
Japan	13	40	3.08	2

Sources: Author‘s own work

3.6. Keyword Co-occurrence and Citation Impact Analysis

Table 9 lists the top 10 author keywords in the fields of AI and traditional music. The most frequent and cited keyword is “deep learning” (16 papers, 11.06 citations per paper). “Music generation” is the most influential topic in terms of average citation count (14.5). Similarly, “neural networks” (12.2) and “folk music” (12.33) also rank high. “DOA estimation” (9.53) and “music (signal processing)” (8.4) highlight the integration of engineering and signal processing with music.

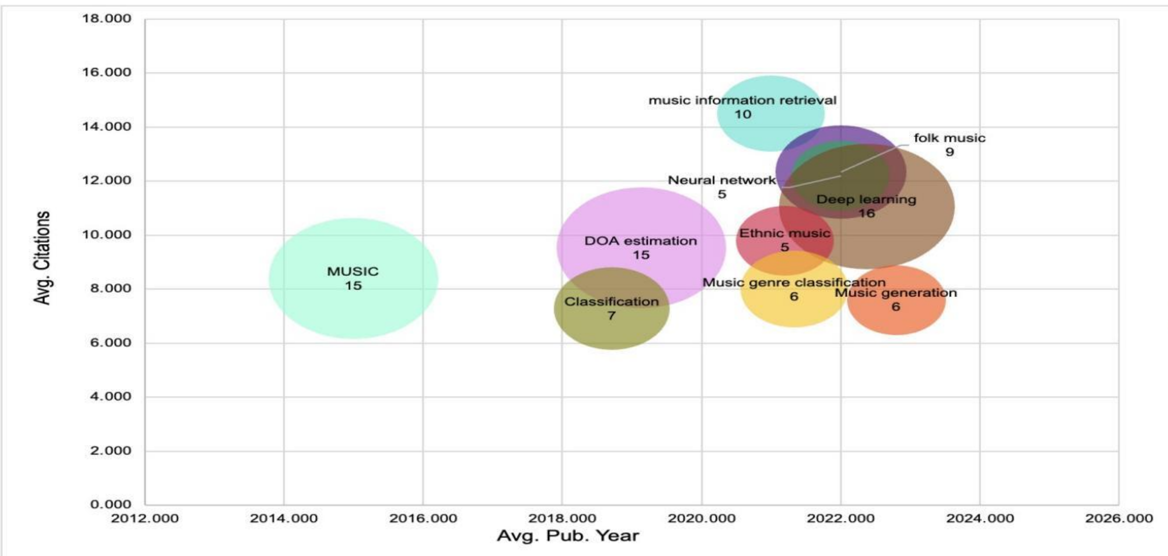
Table 9: High-impact Author Keywords in AI and Traditional Music Research

Keyword	Documents	Avg. Citations	Avg. Publication Year
Deep learning	16	11.062	2022.375
Music generation	6	14.5	2021
Neural network	5	12.2	2022
Folk music	9	12.333	2022
Ethnic music	5	9.8	2021.2
DOA estimation	15	9.533	2019.133
MUSIC (signal processing)	15	8.4	2015
Music genre classification	6	8	2021.333
Music information retrieval	10	6.6	2018.7
Feature extraction	7	5.571	2017.571

Sources: Author‘s own work

Figure 4 visualizes the temporal evolution and topic influence of the most influential author keywords in AI and traditional music research in three dimensions, including the average publication year (X-axis), the average number of citations per document (Y-axis), and the number of documents (bubble size). For example, "deep learning", "folk music", and "neural networks" are located in the upper right quadrant, indicating that they are both recent research topics and highly cited topics - a sign of emerging academic frontiers. In contrast, "music" and "DOA estimation" appear in the left area of the chart, indicating that although they were introduced earlier, they still play an important role. In addition, the bubble size shows that some frequently studied topics (such as "classification") may not correspond to the highest citation influence, highlighting the difference between research popularity and academic influence.

Figure 4: Temporal and Citation Impact of Top Keywords



Sources: Author‘s own work

4. Discussion

This bibliometric study uncovers the evolving trajectory and scholarly configuration of research at the intersection of AI and traditional music over the past five decades. The surge in research output after 2019 marks a notable transition from niche experimentation to mainstream academic engagement. This shift is not only driven by advances in deep learning and signal processing but also by increasing global emphasis on digital preservation of cultural heritage and AI-enabled creative practices. The wide disciplinary spread—from computer science and engineering to humanities and decision sciences—illustrates the field's interdisciplinary nature. However, the dominance of technical disciplines such as computer science and signal processing also highlights an imbalance, where cultural and humanistic dimensions may be underexplored. It suggests a need for deeper collaboration between technologists and domain experts in musicology, anthropology, and cultural studies to ensure methodological richness and contextual sensitivity. The concentration of scholarly influence among a small number of journals and authors points to a relatively centralized knowledge structure. While this may support the consolidation of standards and methodological best practices, it also raises the risk of intellectual homogeneity. Interestingly, journals like the Journal of New Music Research—despite fewer publications—achieved high citation impact, indicating that interdisciplinary platforms may be more conducive to visibility and lasting influence.

In addition, author keyword analysis offers a complementary view of how research frontiers are formed and recognized. High-frequency and high-impact terms such as "deep learning" (C/P = 11.06), "music generation" (C/P = 14.5), and "neural networks" (C/P = 12.2) occupy the top-right quadrant in temporal citation maps, indicating their status as recent and influential themes. These terms highlight the field's turn toward computational creativity and machine-driven reproduction of traditional music styles, often aligned with transformer architectures and multimodal synthesis techniques. Conversely, earlier-introduced but still-cited keywords like "DOA estimation" (C/P = 9.53) and "MUSIC (signal processing)" (C/P = 8.4) underscore the foundational role of engineering methods, especially in applications such as acoustic scene analysis and real-time sound source tracking (Hu et al., 2021; Wan et al., 2021). Their continuing presence in keyword maps confirms the durability of signal-based techniques in evolving AI-music systems. Keywords such as "folk music" and "ethnic music" exhibit high average citation rates (C/P > 9), reaffirming the academic shift toward culturally grounded research. This aligns with efforts to preserve musical heritage through computational means and highlights the value of contextual sensitivity in model design and evaluation (Macintyre et al., 2017; Du et al., 2023). In contrast, frequently studied topics like "genre classification" (C/P = 8) and "feature extraction" (C/P = 5.57) do not correspond to the highest citation impact, suggesting that research popularity does not equate to innovation. This divergence emphasizes the importance of moving beyond methodological repetition toward interdisciplinary creativity an d cultural meaning-making.

Apart from that, the convergence of rapid technical development with increased cultural and ethical awareness marks a critical inflection point for the field. Discussions of data colonialism, authenticity, and inclusive dataset construction (Kanhov et al., 2025; Huang et al., 2023) call attention to the risks of applying AI systems indiscriminately to cultural domains. Responsible AI practices in traditional music must prioritize cultural agency, transparency in model assumptions, and dialogue with local knowledge systems.

5. Conclusion

This bibliometric study systematically examined the evolution of artificial intelligence (AI) applications in traditional music research from 1974 to 2025, analyzing 499 publications retrieved and processed using BiblioMagika®. The results reveal a significant upward trend in both the volume and thematic complexity of research, particularly after 2019. Early studies were mostly fragmented and focused on signal processing techniques, whereas recent work demonstrates the integration of generative AI, cultural modeling, and interdisciplinary innovation. In terms of geographical representation, the most productive and influential contributions originate from East Asia, Europe, and North America, while regions such as Southeast Asia, Africa, and Latin America remain underrepresented. Thematically, technical topics—particularly genre classification and feature extraction—continue to dominate the field, whereas cultural expression, music education, and performance practice receive relatively little attention. Although multimodal research has begun to emerge, most studies still rely heavily on audio-based analysis, overlooking the embodied, visual, and interactive dimensions of traditional music.

This study also has several limitations. The dataset primarily consists of English-language publications indexed by Scopus, potentially excluding valuable works in other languages or those using culturally specific terminology, introducing a risk of linguistic and cultural bias. Additionally, other significant academic repositories such as Web of Science, CNKI, and RILM were not included, which may limit the representativeness of certain regions or disciplines.

In light of these findings and limitations, several directions for future research are proposed. First, researchers are encouraged to explore cutting-edge technologies such as generative adversarial networks (GANs), augmented and virtual reality (AR/VR), multimodal transformers, and style transfer networks to model and preserve traditional music in immersive and adaptive formats. Second, future studies should integrate literature from other databases and non-English sources to capture a more diverse and comprehensive global knowledge landscape. Third, comparative regional studies—for example, across Chinese, Southeast Asian, and West African musical traditions—have great potential for revealing how AI models adapt to different cultural structures.

Ethics Approval and Consent to Participate

This study is a literature-based analysis that does not involve human participants. Therefore, ethical approval and informed consent were not required.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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