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Original Research Article

Mapping the Technological Landscape of Cricket: A Bibliometric Analysis of AI and Sensor Technology in Cricket

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Abstract

Background: Cricket has gradually drifted away from intuition led coaching toward a discipline governed by measurement and computation, propelled largely by artificial intelligence and wearable sensing. Yet the scholarship charting this shift stays scattered across engineering, biomechanics, and sports science, leaving little clarity on how these strands connect. ***Methods:*** This study mapped that terrain through a bibliometric and science mapping exercise. A total of 688 documents indexed in Scopus between 1981 and March 2025 were retrieved using a Boolean title–abstract–keyword strategy, screened under PRISMA guidance, and examined with the R-based Bibliometrix package. ***Results:*** The field showed a modest annual growth of 4.35%, drew contributions from 2,199 authors, and saw roughly a fifth of its output emerge through cross border partnerships. Three phases surfaced long dormancy, gradual momentum after 2005, and a steep climb from 2022. India dominated in volume while the United States commanded citation influence, and the University of Twente anchored institutional productivity. A dual thematic character blended acoustic sensor biology with performance-oriented wearable and machine learning research. ***Conclusion:*** The evidence sketches a maturing yet fragmented field, offering scientists, engineers, and sporting bodies a grounded reference point for where smart cricket inquiry has travelled and where it seems headed.

Keywords: Bibliometric analysis; Cricket; Artificial intelligence; Wearable sensor technology; Sports science; Science mapping; Machine learning; Bibliometrix; Sports engineering.

1. INTRODUCTION

Modern athletic sports have shifted from a thought-based coaching to a highly rigorous, datadriven discipline, a paradigm shift significantly accelerated by the rapid technological advancement [1,31]. Among the major sports niches, cricket presents a uniquely data researched with intensive framework where small details ranging from a fraction of a degree in bowling arm extension to a minute delay in a batting stroke that govern excellent level outcomes [2]. Historically dependent on manual scorekeeping and visual evaluation i.e., subjective in nature by coaches, the sport has undergone a huge technological revolution over the last two decades. This transformation is primarily rooted by two interconnected scientific domains: Artificial Intelligence and wearable sensor technologies [4]. These structural innovations and their implementations have changed how the modern game is played, monitored, decision made for, and commercially broadcasted along length and breadth, worldwide [5,32].

The integration of artificial intelligence in cricket has shifted from basic statistical forecasting to complex, real time analytics [6]. Computer vision algorithms and advancements in machine learning architectures now form the foundational pillars of predictive and intuitive match simulation, automated field placement and location optimization, and deep learning driven by player performance profiling [7]. For example, complicated predictive models continuously process historical measurements, environmental pitch variations, and weather indices to accurately represent possible game trajectories [8]. Altogether simultaneously, computer vision systems are extensively used to rectify the technical mechanics by automatically processing high speed video footage to differentiate into parts and isolate structural flaws in footwork, wrist orientation, and biomechanical posture [9]. Beyond athletic performance, Artificial intelligence has redefined fair play through improved and advanced officiating workflows, offering real time ball locating and trajectory projection systems that dramatically reduce human refereeing faults and loopholes.[10].

Along with software driven intelligence, hardware advancements and improvisations seen in Micro Electro Mechanical Systems have helped and proliferated the use of wearable sensors and "smart" sports equipment [11]. The miniaturized devices like, Inertial Measurement Units, tri axial accelerometers, gyroscopes, and magnetometers deployment has effectively turned the cricket pitch into a, a true field of research.[12]. Commercial bat sensors track parameters like back lift velocity, follow through angles, and twist, translating kinetic output into localized data streams that help to assess and evaluate. [13]. Similarly, the smart instillment of smart cricket balls embedded with encapsulated telemetry chips allows sports biomechanic to measure and convert torque to spin conversions in a multi-dimensional matrix [14]. For fast bowlers, who undergo extreme physical challenges via complex rotational spinal forces, Global position systems installed in vest trackers and wearable skin patch sensors continuously log internal and external workloads, providing important telemetry to predict and spread information to users regarding soft tissue or lumbar injuries in order to prevent the injuries [15].

In spite of this exponential increase in the field of scientific publications detailing isolated components of cricket technology, the academic literature remains highly diversified and fragmented [16]. Computer engineers have researched and have frequently published highly technical algorithmic validations without relating to real world sports science implications, while sports biomechanic personnel publish localized clinical interventions that overlook and tend to miss out on broader macro trends in machine learning field which is everchanging [17]. An overall knowledge forming how these dysfunctional domains bring in topics and share them in common, evolve, and cooperate globally maintaining a critical knowledge gap [18]. Earlier bibliometric assessments in sports medicine have extensively paved a path to generic injury measuring spread in different geographic parts or isolated sub disciplines like sports marketing [19]. On the contrary no one have in total evaluated the intellectual, social, and structural evolution of advanced technological infrastructure specifically within cricket.

To bridge this gap observed in analysis, this study conducts a comprehensive bibliometric and science mapping analysis using high stringency metadata extracted from premium indexing databases like Scopus. By activating and using advanced technologies like computational bibliometric instruments specifically R package Bibliometrix. This paper systematically quantified global publication possibilities in length and breadth, identified key institutional clusters, focuses inter country collaborative networks, and helps to differentiate into sub categories and segregate into latent thematic structures within the field. Finally, this study aims to provide sports scientists, engineers, and institutional stakeholders with a rigorous reality check of the existing milestones, trending topics, and developing frontiers governing the technological aspect of cricket.

2. METHOD AND MATERIAL

2.1 Data Extraction Search Approach

The R-studio was used to conduct the bibliometric analysis. The electronic database that has been exclusively selected for this study was Scopus. [21]. To record and capture all relevant academic literature, the process of data retrieval targeted the main metadata components of indexed publications: Title, Abstract, and Keywords (TITLE-ABS-KEY). The specific search query pathway was constructed by providing the discrete parameters that were outlined by the investigator, utilizing Boolean operators (AND, OR) to maximize search sensitivity while narrowing down on diversifications while removal of equivalent technological terminology. The review specifically targeted studies on Cricket and Technology published in English language from the time period of 1981 to March, 2025, ensuring that the findings mentioned the most recent advancements in the field. The electronic search was conducted on March 3, 2025, following the predefined search term: (TITLE-ABS-KEY (“cricket”) AND (TITLE-ABS-KEY) (“Artificial Intelligence") OR ("AI") OR ("Sensor") OR ("Sensor Technology") OR ("Technology") OR ("Wearable technology”).

2.2 Inclusion and Exclusion Criteria

To ensure the ability to use the search layout later as a preset data for network analysis, strict eligibility thresholds were enabled prior to data collection [27].

2.2.1 Inclusion Criteria:

1. Exclusively the data has been indexed only within the Scopus Database.
2. Title, Abstract, and Keywords (TITLE-ABS-KEY) were used to strictly extract the Metadata.
3. Documents that have been published lied within a 44 year window (1981–2025).
4. Publications that are written are elicited entirely in English Language.
5. Peer reviewed original research articles along with full conference proceedings were included.
6. Studies analysing advanced software like AI, Machine Learning or hardware like sensors, wearables were applied directly to Cricket.

2.2.2 Exclusion Criteria:

1. Secondary indexes or aggregators that are not commercially publishing i.e. outside Scopus.
2. Elimination of articles where Full text matches where terms appeared only in footnotes, references, or general text body.

3. Documents published before 1981 or after March, 2025 were excluded from the collection of data.
4. Publications in any other language except for English or articles missing translation metadata were excluded.
5. Letters, editorials, book reviews, short notes and pre print abstracts.
6. Documents missing a valid Digital Object Identifier, in order to prevent deduplication and traceability.
7. Documents with unlisted, confusing, or missing affiliation metadata were shortlisted and eliminated from collection of data.
8. Irrelevant Homonyms e.g., biological research on the cricket insect or general industrial sensor engineering.

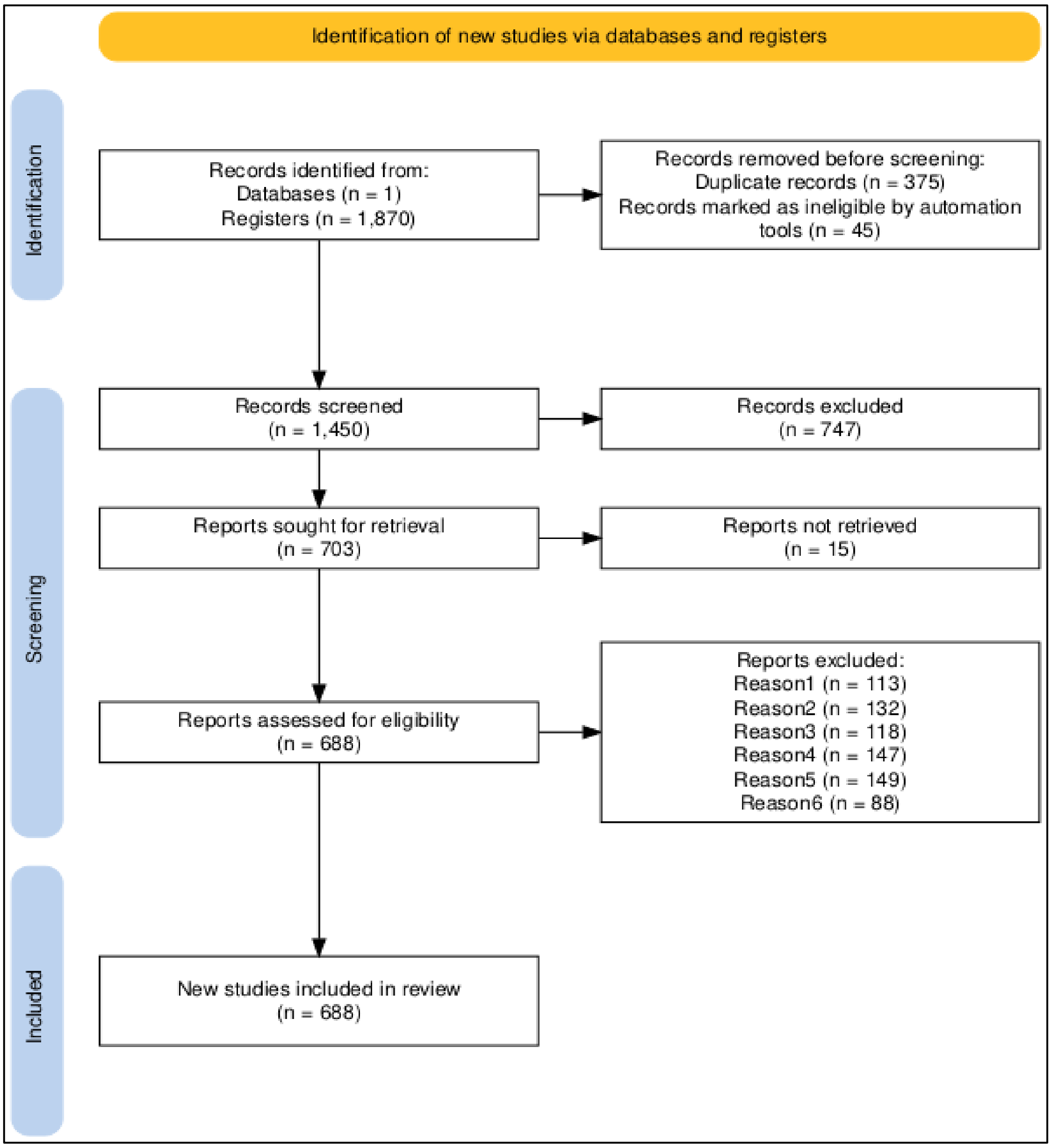

Fig. 1: PRISMA Flow Diagram

PRISMA Flow Diagram

A total of $n = 1{,}871$ raw records were identified from the primary search query, from Scopus database and $n = 1{,}871$ via registers. Before entering the formal screening stage, a subset of records were systematically filtered out. Duplicate records removed: $n = 375$,Records marked as ineligible by automation tools: $n = 46$, Following these automated deductions, a total pool of $n = 1{,}450$ records finally shortlisted for manual screening. Out of the $n = 1{,}450$ records were checked for thematic relevance, $n = 747$ records were excluded for failing to meet the main aim of the study. This left $n = 703$ reports were considered as data collected. Among these, $n = 15$ reports could not be successfully retrieved due to institutional access barriers or missing full text files, leaving $n = 688$ reports successfully obtained. The remaining $n = 688$ reports were subjected to an gruelling eligibility review. During this process, records were cross checked against the mentioned exclusion criteria (such as missing DOIs, anonymous authors, or irrelevant document types). The exact exclusion distribution was recorded as follows:

Reason 1 being publications other than English Language $n = 113$

Reason 2 Publications with Missing Author and Anonymous Data: $n = 132$

Reason 3 Publications with Missing Registered Digital object identifier: $n = 118$

Reason 4 Publications with Incomplete Affiliation or Country Data: $n = 147$

Reason 5 Allowance of Document Type like Edits or Letters were barred: $n = 149$

Reason 6 Entomological Homonym Cricket Insect Noise: $n = 88$

As explained in the final stage of PRISMA guidelines, after summing up the total exclusions, a total of $n = 688$ new studies completely satisfied all strict criteria.

3. RESULTS

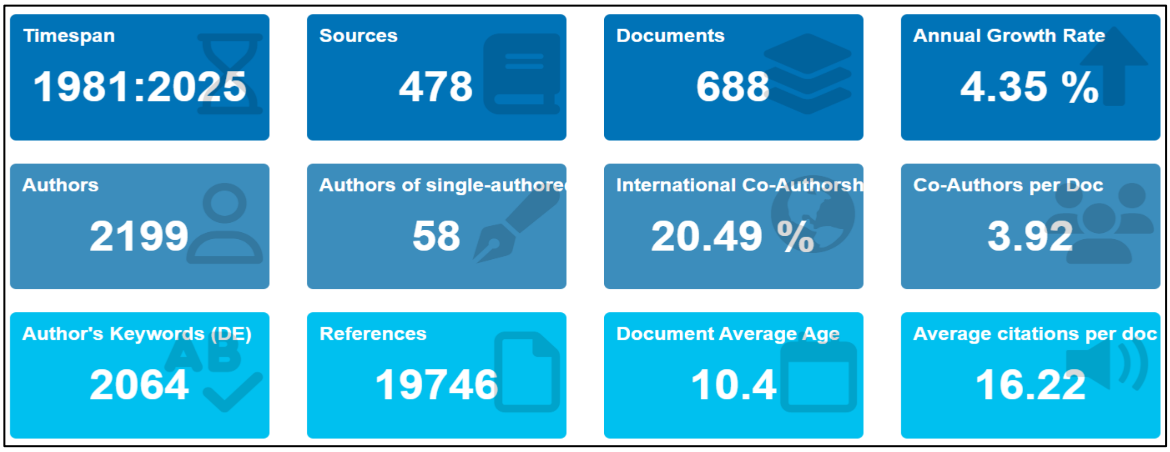

Fig. 2: Over View of the Study

3.1 Over view of the study

The bibliometric analysis covered 688 publications that were indexed in 478 sources over the period of 1981–2025. The field successfully showed a steady annual growth rate of 4.35%, also brought to light the increasing research interest. A total of 2,199 authors contributed to the literature, with only 58 single authored publications, pointing out a strong collaborative research culture. The average number of co-authors per document was 3.92, while 20.49% of the studies involved collaboration from international level. The dataset included 2,064 author keywords and 19,746 references. The average document age was 10.4 years, and the publications received 16.22 citations per document explaining in detail the moderate scientific impact and sustained relevance of scholarly importance Fig.2.

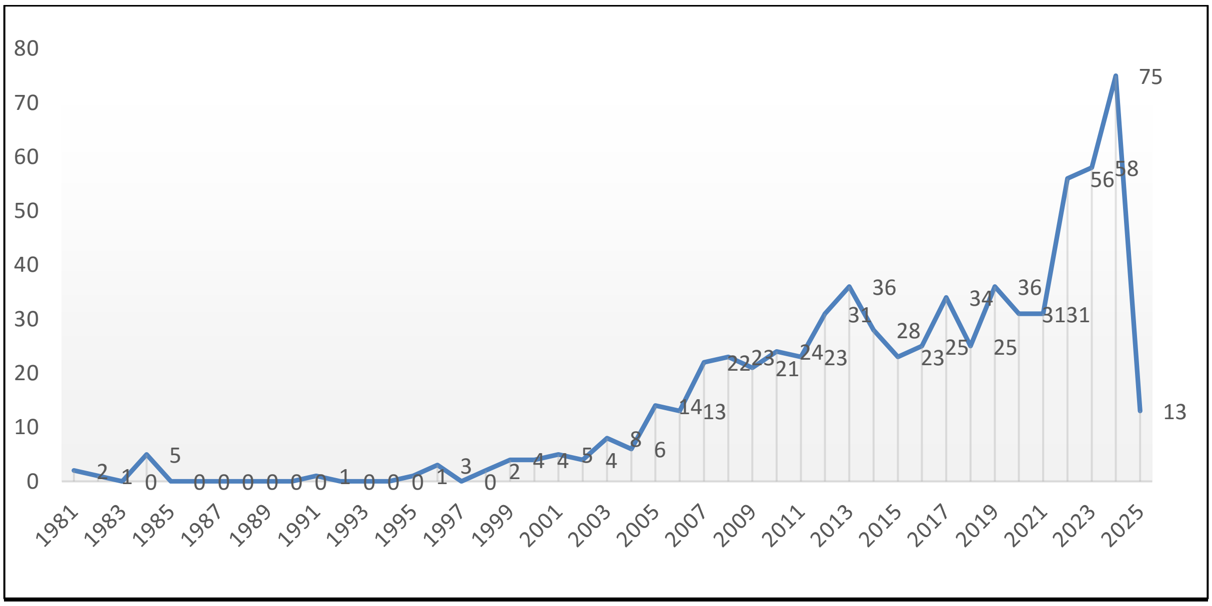

Fig. 3: Annual trend of Scientific production

3.2 Annual Scientific Production

Three distinct phases have been displayed in this annual scientific production trend. From 1981 to 2004, research remained sustained, rarely exceeding single digits. A steady growth phase emerged between 2005 and 2021, ranging fairly between 13 and 36 articles yearly. Finally, an exponential surge occurred from 2022 onwards, peaking at 75 publications in 2024.That was a skyrocketing change observed and documented.

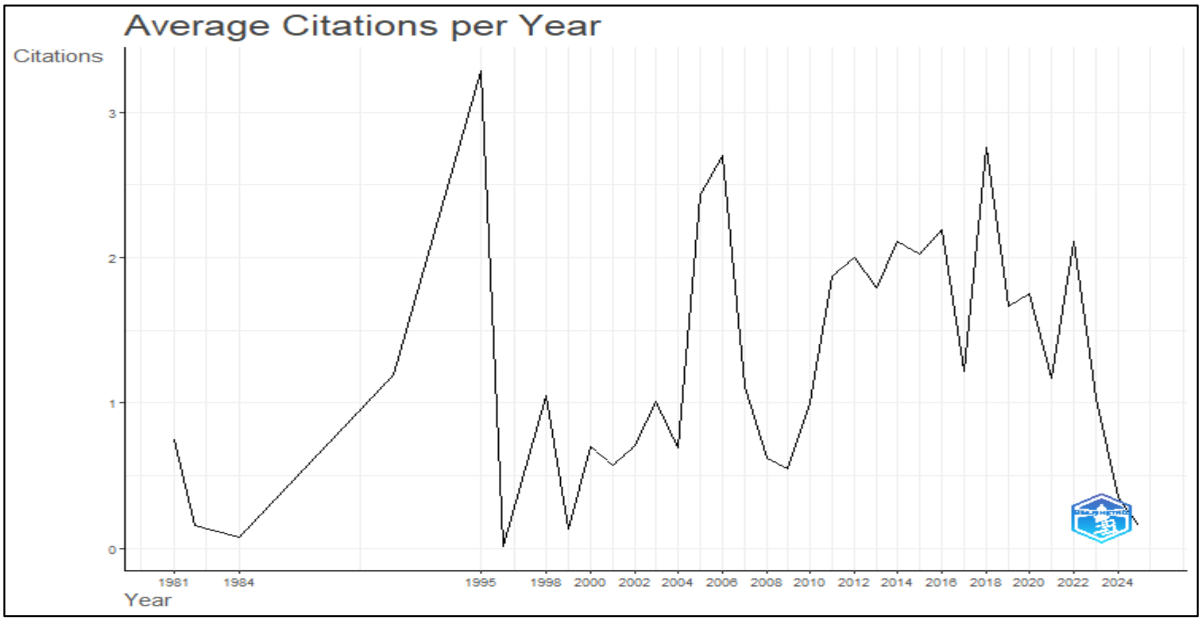

Fig. 4: Average Citation Per Year Based on aforementioned data highlights citation impact metrics alongside annual publication counts (N). While publication volume reached its top significantly in 2024 ($N = 75$), the Mean Total Citations per article (MeanTCp) reached its highest historical valuation in 1995 at 105

3.3 Average Citation Per Year

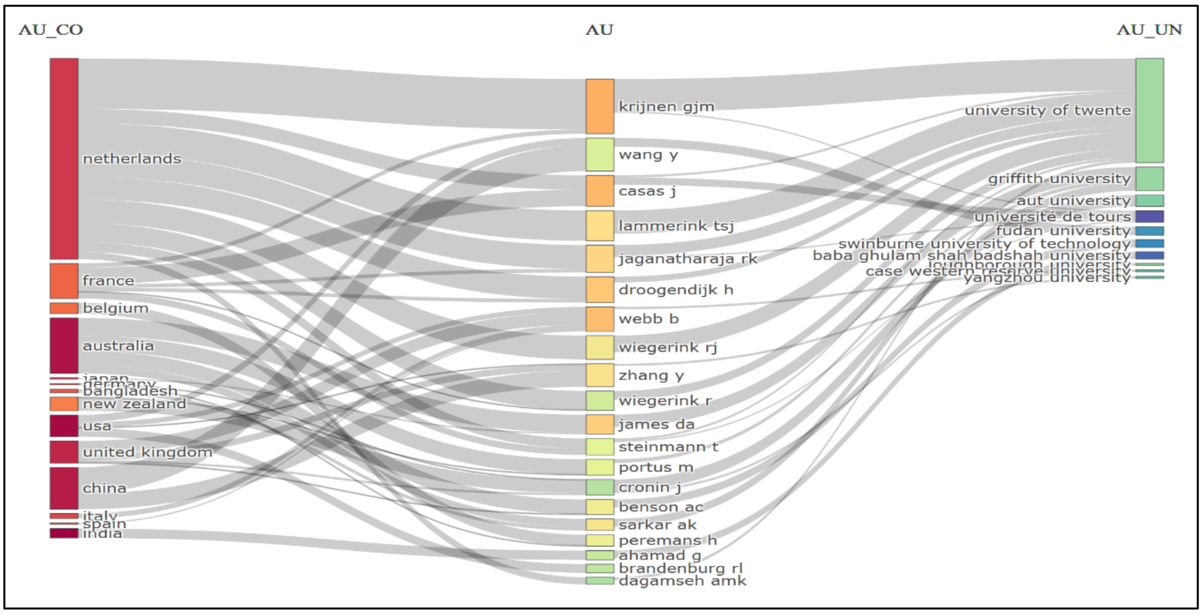

Fig. 5: Three Fields Plot

3.4 Three Fields Plot

The three fields plot in figures and graphs out the collaborative connections linking Authors' Countries (AU_CO), Authors (AU), and Institutional Affiliations (AU_UN). The Netherlands serves as the pivotal research hub, heavily driven by authors like Krijnen GJM at the University of Twente. Key global contributions also emerge from influential institutional groups across Australia, France, China, and the United Kingdom.

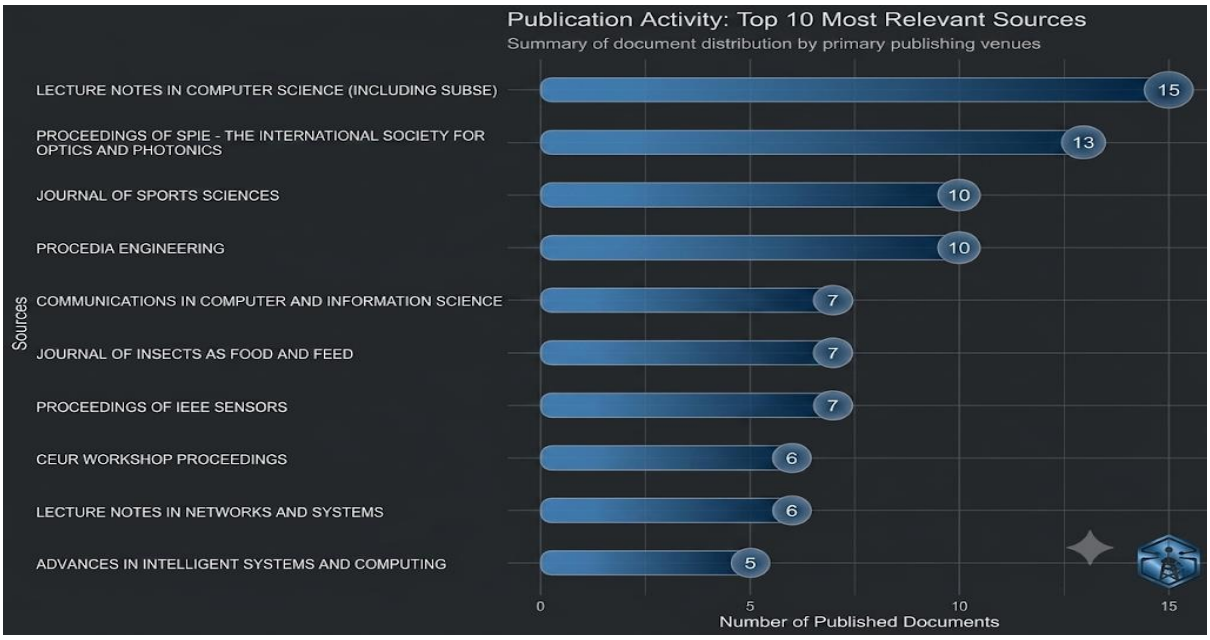

Fig. 6: Top 10 Most Relevant Source

3.5 Most Relevant Source

The publication activity chart highlights the top 10 most relevant sources for the dataset. Lecture Notes in Computer Science leads with 15 published documents, followed by Proceedings of SPIE with 13 articles. Core domain results are further distributed across engineering, computer science, sports analytics, and entomological literature matrices.

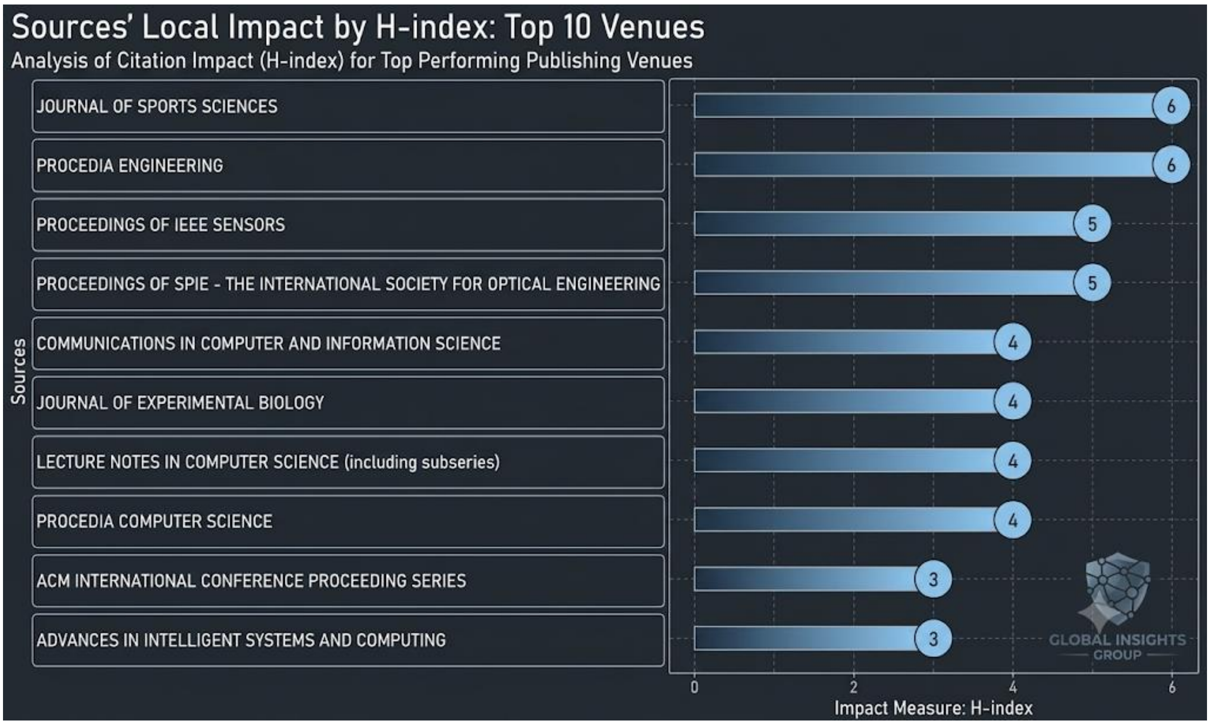

Fig.7: Top 10 Sources of Local Impact by H- Index

3.6 Source of Local Impact

H indication has been used in the above chart to measure local citation impact across the top 10 publishing venues. Journal of Sports Sciences and Procedia Engineering are the journals that lead the dataset, both achieving the highest H-index of 6. High end performing technical tracks like Proceedings of IEEE Sensors and Proceedings of SPIE concurrently ascend and stay with an H-index of 5.

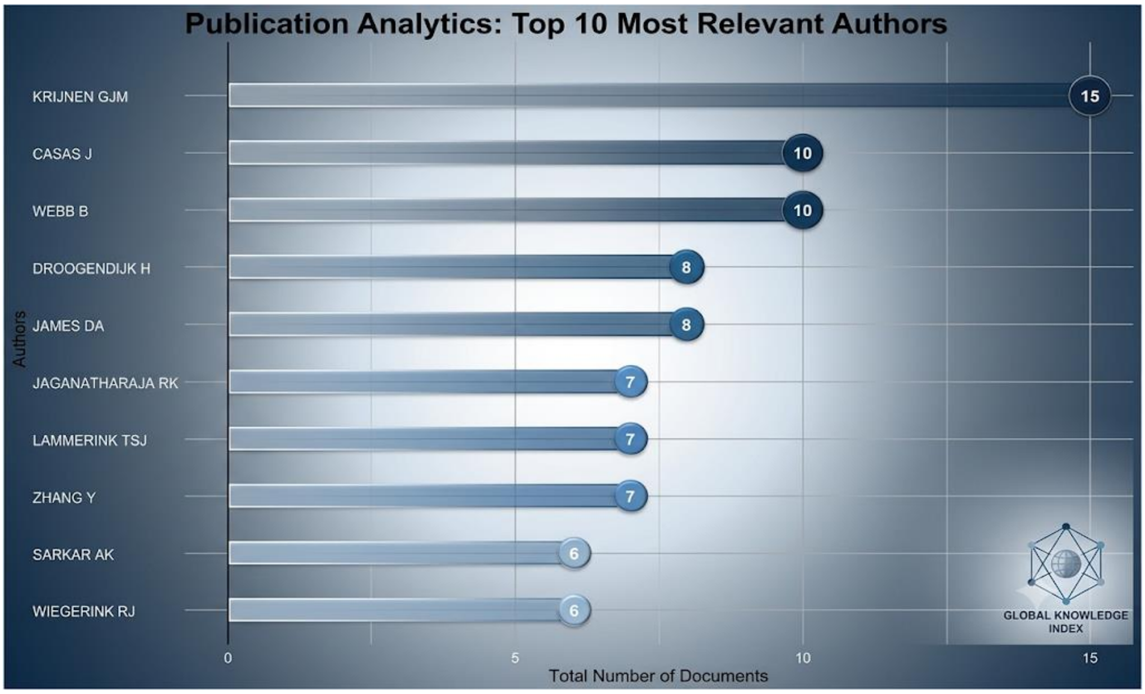

Fig. 8: Top 10 Most Relevant Source

3.7 Most Relevant Author

The publication analytics chart shown above has reached the rank of the top 10 most relevant authors by their volume of work. Krijnen GJM is the most eminent contributor with 15 documents. Casas J and Webb B are related closely with 10 publications each, while the remaining other scholars show a steady output ranging from 6 to 8 documents.

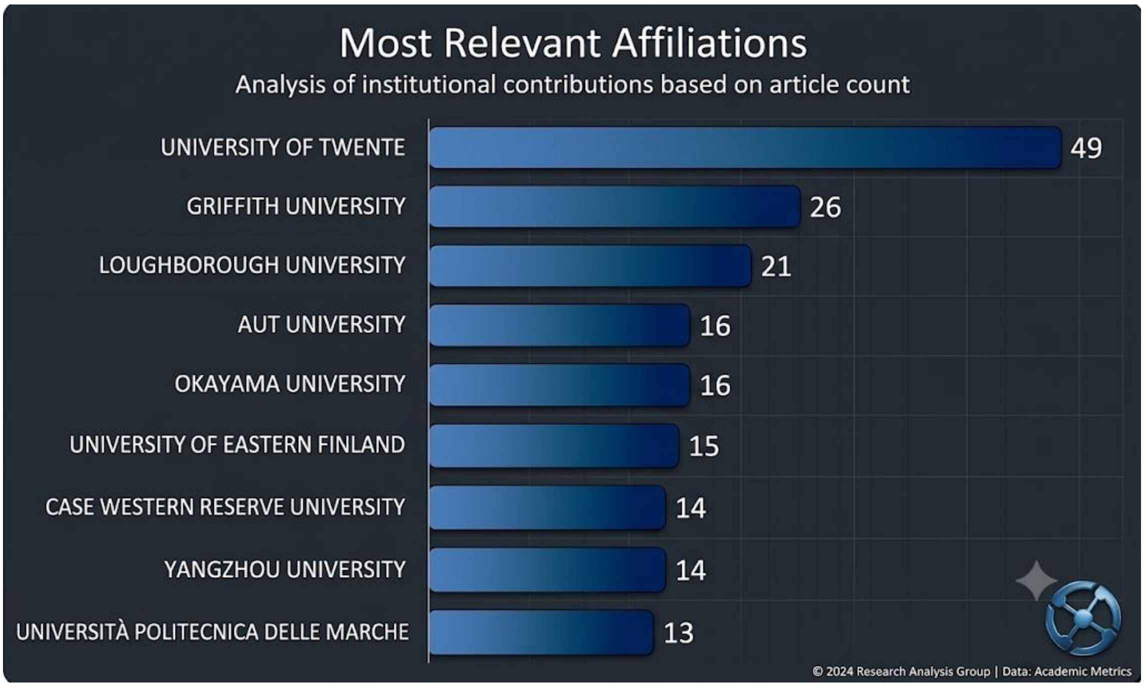

Fig. 9: Top 10 Most Relevant Affiliation

3.8 Most Relevant Affiliation

The most relevant academic affiliations are shown in the above display. These academic affiliations have been ranked by their total article contributions. The University of Twente leads the dataset with 49 articles with powerful dominance. Griffith University standing second with 26, and Loughborough University holds 21. The remaining listed global institutions provide a relatively close group range of 16 to 13 articles.

Fig. 10: Top Most Cited Country

3.9 Most Cited Country

The top 10 most cited nations by country origin are ranked in the global citation leaderboard above. The academic landscape has been dominated highly by US with 2,402 citations, followed by Australia with 1,148 citations. The third place has been secured by United Kingdom with 670 citations, while the remaining nations accumulate values between 246 and 464.

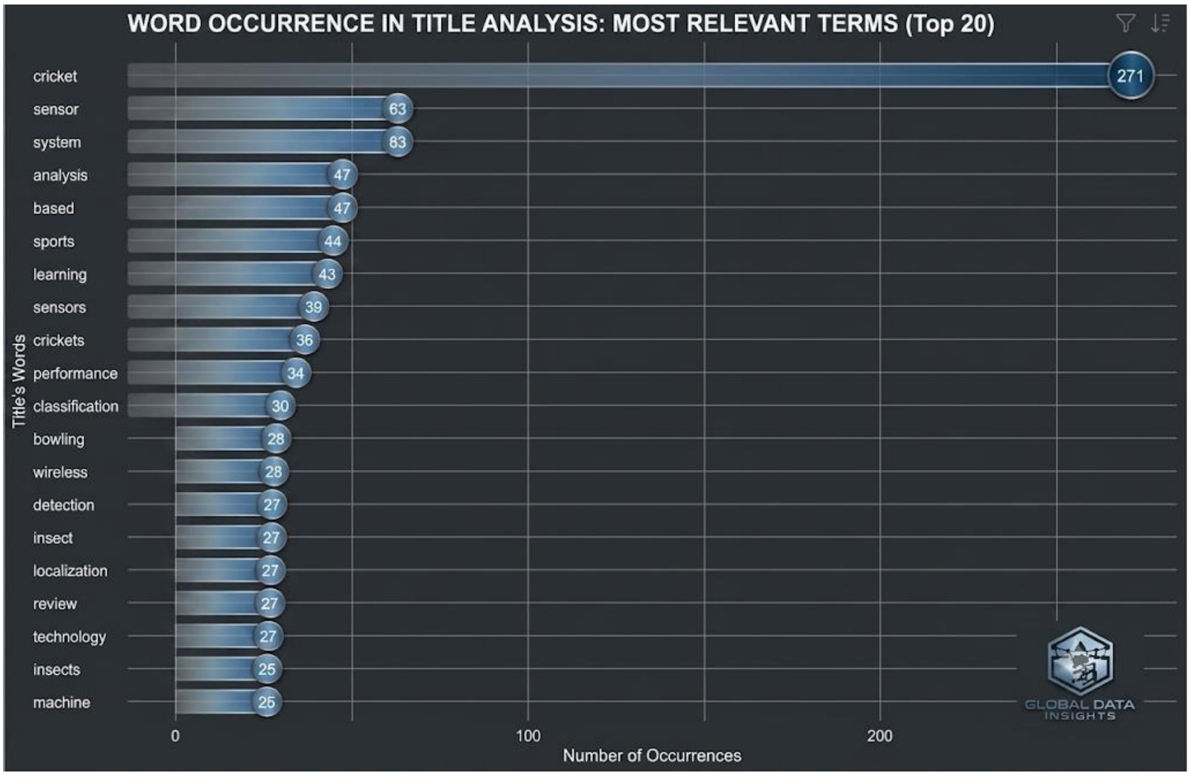

Fig. 11: Top 20 Most Relevant Word

3.10 Most Relevant Word

The above word occurrence analysis graph identified the top 20 most relevant terms used in publication titles. "Cricket" being the dominant with 271 occurrences. Other being second are technical and analytical keywords that are chronologically following are “sensor" and "system" at 63 occurrences each, alongside recurring terms like "analysis", "based", "sports", and "learning".

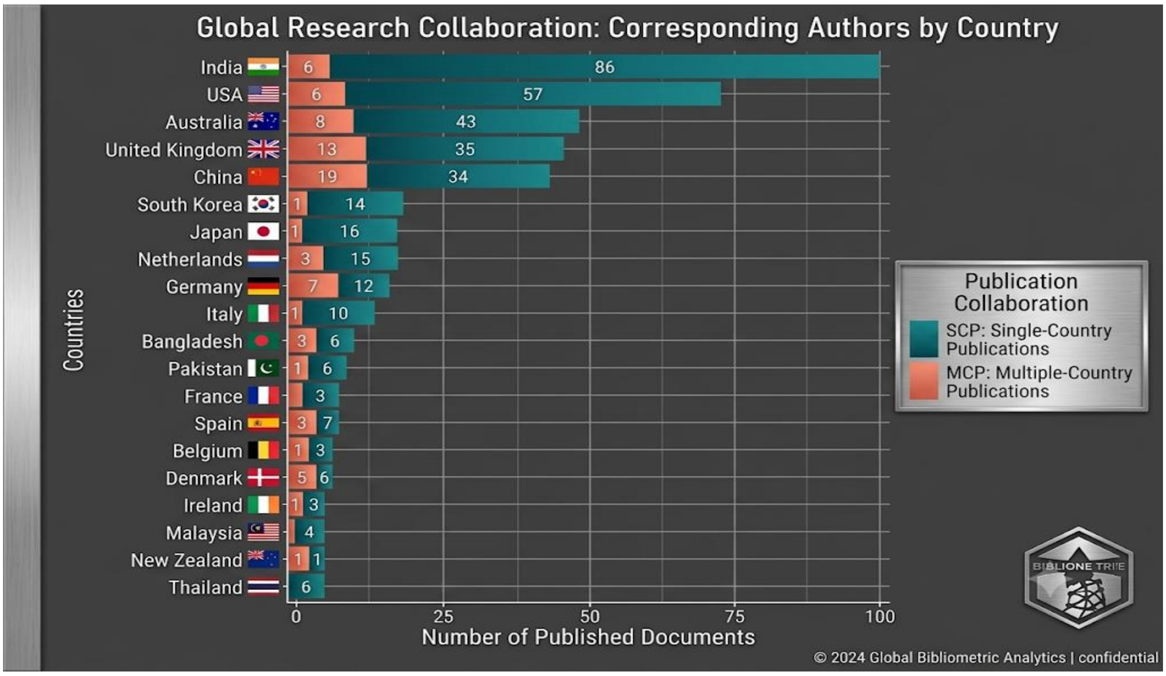

Fig. 12: Collaboration of Corresponding Authors Country

3.11 Corresponding Authors Country

Global research collaboration are being broken down in the above chart by corresponding authors' countries. India is seen to lead the dataset with 86 single country publications (SCP) and 6 multiple country publications (MCP). The USA and Australia are second as key hubs, while China shows the highest relative cross border collaboration with 19 multiple country publications.

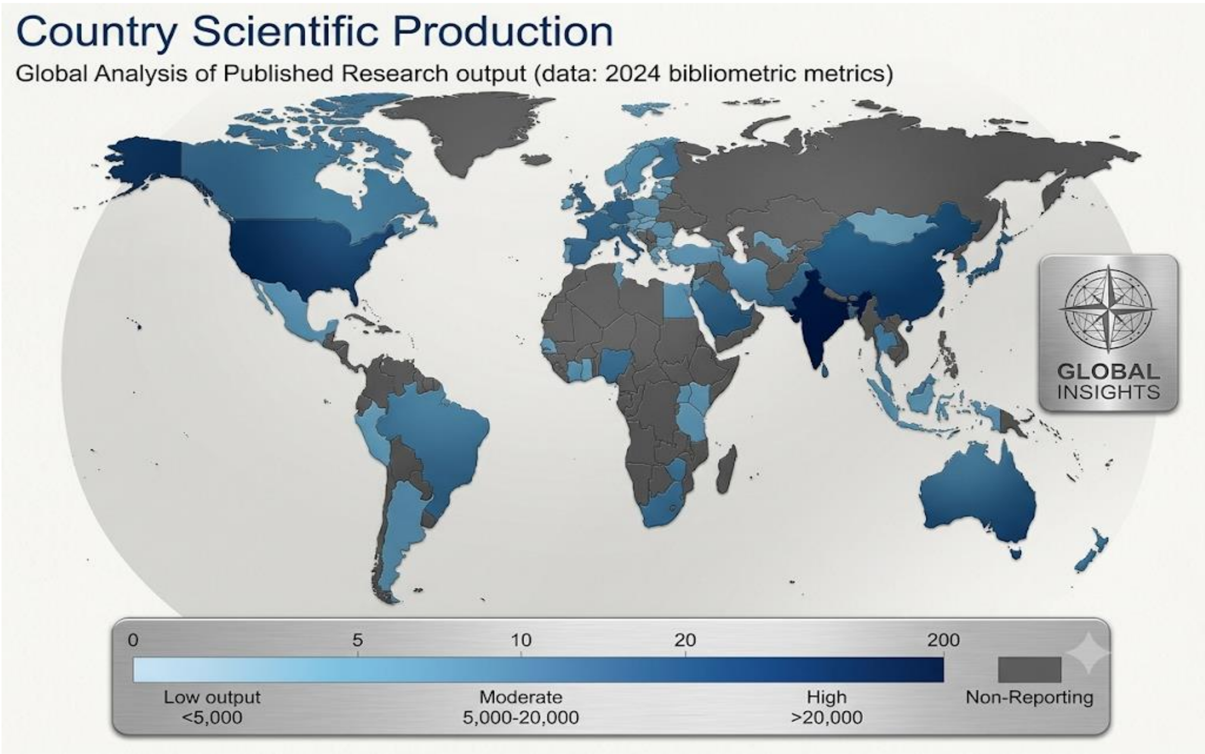

Fig. 13: Country Scientific Production

3.12 Country Scientific Production

The above global choropleth illustrates production specified on countries based on 2024 bibliometric measurements. India is marked with the highest research output density, coloured by the deepest shade of blue. The USA, China, and Australia also serve as primary global contributors, while equally important portions of Africa and South America remain non reporting.

4. DISCUSSION

The bibliometric findings of this study provide detailed information of how Artificial Intelligence (AI) and wearable sensor innovations have gradually been interrelated with cricket literature over a 44-year period. The overall trajectory illustrated in the annual scientific production highlights a clear, technology driven evolution. Stagnation has been long observed between 1981 and 2004 that depicts the era when both microelectronics and computer learning models were expensive and impractical and structurally heavy, making them unsuitable for real time sports execution [4, 11,40]. The steady increase after 2005 corresponds directly with the spread of commercialized use of micro electro mechanical systems (MEMS) such as miniaturized tri axial accelerometers and high-speed broadcast cameras [12,41]. Finally, the exponential increase from 2022 onwards proved that sports engineering has entered a mature phase, geared up by ultra-modern edge computing, automated computer vision networks, and advanced wearable devices with opportunities. [1, 9,39].

The affiliation measurement parameters of institute and at country level reveal a compelling geographical and structural variation that is not similar pattern but dynamic. India and Australia are considered to be the traditional cricket playing nation which is featured heavily as primary centres of single country and corresponding author production. India's status remains prominent in overall dimensions correlates with the massive commercial and institutional support provided by elite leagues like the Indian Premier League popularly known as IPL, which actively fund predictive game simulation, also advanced techniques like machine learning talent identification trackers, and data platforms for fan engagement [7, 20,38]. Surprisingly, while the USA is not a traditional test cricket nation, its massive citation dominance i.e. 2402 citations highlighting its role as a fundamental developer of base machine learning architectures, computer vision tracking algorithms like Hawk Eye foundational logic, and biometric sensors that sports scientists have been planning on to adapt to cricket later [6, 13,37].

Sources of publications and their activities indicate an interesting interdisciplinary conflict amongst the available literature. Lecture Notes in Computer Science and Proceedings of SPIE that are core engineering and data storage sites currently lead the overall distribution of document, whereas sports centred outlets like the Journal of Sports Sciences hold the highest local impact with H index of 6. This gap marks a pivotal changing phase in the field. While data engineers often publish technical validations against algorithms or calibrations that are structurally sensor based, specialists on sports biomechanics added value to these tools to make impactful clinical interventions, check for fast bowling spinal duress, or improve real time batting back lift mechanics [2, 14, 15, 35,36].

The title word occurrence and three fields network analyses reveal a dual intellectual structure in the literature that requires changes to be brought with utmost care. An adequate portion of data of historical cricket links to biological research studying the fine thread like details of mechanics and wind receptive design that are highly sensitive industrial acoustic sensors [18]. On the other hand, the modern sports science branch focuses on implementation and adding inertial measurement unit IMU, wireless telemetry, and deep learning classification altogether to objectively plan on improving human athletic performance on the pitch [12, 16,33,34]. This evolution brings out that the introduction of advanced technology in cricket is shifting away from engineering platforms toward collaborative, real world sports science ecosystems.

5. CONCLUSION

This study claims to be the first comprehensive bibliometric analysis that have included the intellectual, social, and geographic evolution of Artificial Intelligence and sensor technologies within the sport of cricket from the period of 1981 to 2025. By forming an analysis of a clean dataset of 688 peer reviewed documents, the study shows how cricket has evolved from a game assessed through coaching observation that was subjective in nature into a highly sophisticated, data driven sports science framework.

With the main objective of workflow to optimize player performance profiling, provide real time batting telemetry, and manage fast bowling workloads to minimize injury risks there have been a huge transition from complete hardware focused sensor implementation to modern integration of machine learning and this is highlighting the structural evolution. Geographically diverse yet both the countries India and USA are considered to be hubs for knowledge of cricket but cricket centric nations like India lead in publication volume and single country research and USA just focuses on foundational algorithm citations. In addition, the need for research has been discovered as research will bridge the gap between technical engineering with the help of practical coaching applications. The basis of this discovery remains to be high citation impact.

With the continuation in advancing emerging technology like edge computing, smart-equipment integration, and creative in generation of player tracking models, this bibliometric map offers sports scientists, electronics engineers, and high-performance sporting bodies a clear, documented roadmap of the achieved ideas and emerging domains within the smart cricket landscape.

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