Mapping the Convergence of Artificial Intelligence, IoT, and Embedded Systems: A Comprehensive Bibliometric Analysis (2015–2025)

Mohamed NOUAYTI [1)] , Anass AYNAOU [2)] , Nordine NOUAYTI [2)] , Younes ADNANI [1)]

[1)] *Department of Business Administration, Politeknik Negeri Madiun, Madiun, Indonesia*

[1)] contact@uit.ac.ma

[2)] *Environmental Management and Civil Engineering Team, Applied Sciences Laboratory, National School of Applied Sciences, Abdelmalek Essaadi University, Al Hoceima, 32002, Morocco*

[2)] support.ensah@uae.ac.ma

Abstract:

Background: The rapid convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and Embedded Systems has birthed the era of "Edge Intelligence." Current knowledge indicates a fundamental technological pivot where intelligence is moving away from centralized cloud architectures toward decentralized, autonomous, on-device processing.
Objective: The study aimed to map the global research landscape, identify key scientific contributors, analyze collaboration networks, and track the thematic evolution of Edge Intelligence research between 2015 and 2025.
Methods: This study utilized a quantitative bibliometric methodology and scientific mapping. A corpus of 2,623 peer-reviewed documents was extracted from the Scopus database and analyzed using specialized software tools, namely R-Bibliometrix and VOSviewer.
Results: The findings reveal an extraordinary annual research growth rate of 61.21%. While China is the quantitative leader in total citations, countries like Australia, the UK, and the USA demonstrate the highest qualitative impact per publication. The IEEE Internet of Things Journal was identified as the most influential venue. Thematically, the field has shifted from "cloud-centric AI" to "on-device intelligence," powered by breakthroughs in TinyML and FPGA optimization, with a rising focus on data privacy, green computing, and network security.
Conclusion: The results confirm a paradigm shift toward autonomous cyber-physical systems, successfully identifying the "gatekeepers" and emerging frontiers of the field. Future research should explore the integration of non-functional requirements, such as energy efficiency and ethics, into the next generation of edge devices.

Keywords: Edge Intelligence, Bibliometric analysis, Internet of Things (IoT), Science mapping, TinyML, Cyber-physical systems.

I. INTRODUCTION

The contemporary technological landscape is defined by a deep-seated convergence between the Internet of Things (IoT), Embedded Systems, and Artificial Intelligence (AI). This triad forms a sophisticated ecosystem where the IoT serves as the "nervous system" for global connectivity, Embedded Systems provide the "physical body" of hardware, and AI acts as the "brain" enabling localized cognition [1]. This synergy has catalyzed the rise of "Edge Intelligence," a paradigm shift that migrates data processing from centralized cloud infrastructures to resource-constrained devices at the network's periphery [2].

The momentum toward decentralized intelligence is fueled by the rigorous demands of next-generation applications, including autonomous robotics, smart clinical monitoring, and Industry 4.0 automation. In these high-stakes environments, traditional cloud-centric frameworks often struggle with latency bottlenecks and data sovereignty concerns. Consequently, the field of "TinyML" has emerged as a critical research frontier, focusing on the deployment of complex neural networks on low-power microcontrollers [3]. However, achieving this requires overcoming the persistent "latency vs. accuracy" trade-off through innovative hardware-software co-design [4].

Despite the exponential growth of this multidisciplinary domain, the scholarly landscape remains fragmented. Current literature reveals a significant research gap: while several bibliometric studies have explored these pillars in isolation—focusing solely on IoT security, general AI trends or Edge Computing without an embedded focus, there is a lack of comprehensive mapping that synthesizes the intersection of all three [5]. Previous reviews, such as those by [6] or [7] , now lack the temporal depth to capture the rapid advancements in localized AI optimization and energy-efficient architectures seen in the last three years ([1], [3]).

This study addresses these shortcomings by providing a holistic bibliometric mapping of the AI-IoT-Embedded convergence over the last decade (2014–2024). Unlike prior works that rely on qualitative summaries, this research employs a dual-tool quantitative approach using R-Bibliometrix and VOSviewer on a curated dataset of 2,623 documents from the Scopus database [1]. The primary objective is to delineate the thematic evolution of the field, identify leading clusters of international collaboration, and highlight emerging frontiers in autonomous cyber-physical systems. By doing so, this paper contributes a strategic roadmap for researchers and stakeholders, offering a clearer understanding of how decentralized intelligence is being institutionalized across global scientific discourse [8].

II. Litterature review

Technological factors can vary, but in the context of the convergence between AI, IoT, and embedded systems, it is common to consider decentralized processing, hardware-software optimization, and non-functional requirements (such as security and energy efficiency). The contemporary technological landscape is defined by a paradigm shift where intelligence migrates from centralized cloud infrastructures to the network's periphery [9]. In this triad, the IoT serves as the "nervous system," while AI acts as the "brain," enabling localized cognition [4].

The first consideration regarding the adoption of Edge Intelligence is decentralized processing. To meet the rigorous demands of next-generation applications like autonomous robotics or Industry 4.0, intelligence must move away from cloud-centric frameworks to avoid latency bottlenecks and address data sovereignty concerns [10]. Previous empirical works have proved that the ability to process data on-device significantly influences the efficiency of autonomous cyber-physical systems [11].

The second factor is hardware-software optimization, particularly through the emergence of "TinyML." Due to the resource-constrained nature of microcontrollers, deploying complex neural networks requires overcoming the persistent "latency vs. accuracy" trade-off [12]. High-impact research indicates that breakthroughs in model compression and FPGA optimization are crucial for the practical deployment of AI on low-power hardware [13], [14].

Furthermore, the integration of non-functional requirements, such as data privacy and "green computing," has become a critical research frontier [15]. Introducing localized AI without considering energy efficiency and network security can impede the sustainability of edge devices [1]. Prior studies indicate that the alignment between hardware design and cognitive software significantly raises the likelihood of system adoption in sensitive environments like smart healthcare. Therefore, several hypotheses are proposed as follows:

H1: Decentralized processing has a positive significant influence on the adoption of Edge Intelligence.

H2: Hardware-software optimization (TinyML) has a positive significant influence on the deployment of embedded AI systems.

H3: Enhanced security and energy efficiency have a positive significant influence on the sustainability of autonomous cyber-physical systems.

III. Methods

A. Database Selection and Data Retrieval Strategy

The empirical foundation of this research is based on a systematic collection of metadata harvested from the Scopus database [16]. Scopus was strategically selected as the primary repository due to its comprehensive indexing of high-impact journals in the fields of Engineering and Computer Science, surpassing other databases like PubMed or Web of Science in terms of technical volume and interdisciplinary coverage [17].

To ensure the relevance of the results, a complex Boolean search string was constructed. The query was designed to capture the intersection of three fundamental pillars: hardware (Embedded Systems), connectivity (IoT), and intelligence (AI) [18]. The search string applied to Titles, Abstracts, and Keywords was:

(TITLE-ABS-KEY ("embedded system*" OR "microcontroller*" OR "edge computing") AND ("IoT" OR "Internet of Things" OR "IIoT") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "TinyML"))

B. Inclusion and Exclusion (Refining the Dataset)

To maintain a high standard of data quality, several filtering layers were applied. Initially, only "Articles" and "Conference Papers" were considered, as these formats undergo rigorous peer review and represent the most up-to-date scientific contributions. "Review" papers and "Chapters" were excluded to focus on original research results [19].

Furthermore, the search was limited to documents published in English to facilitate a standardized global analysis [20]. The subject areas were restricted to "Computer Science" and "Engineering" to eliminate noise from unrelated fields. After the initial retrieval, a manual screening of the metadata was performed to remove duplicates and irrelevant entries [21]. This process resulted in a final dataset of 2623 documents, which were exported in csv file, and Plain Text formats for computational processing [22].

C. Bibliometric Software and Data Processing Workflow

The analytical framework of this study was implemented using a multi-tool approach to provide both quantitative and qualitative insights:

RStudio and the Bibliometrix Package: The core statistical analysis was conducted using the Bibliometrix R-package through its web-based interface, Biblioshiny [23]. This tool allowed for the calculation of performance metrics, including the annual growth rate of publications, most relevant sources (h-index, Bradford's Law), and the most productive authors and institutions [24].

VOSviewer (Version 1.6.3): For science mapping and visualization, VOSviewer was utilized. This software specializes in building and visualizing bibliometric networks based on co-citation, bibliographic coupling, and co-occurrence of keywords. It allowed the researchers to identify "clusters" of innovation and visualize the social structure of international collaborations through network maps [25].

This dual-software strategy ensures a robust triangulation of data, combining statistical rigor with advanced visual mapping [26].

D. Justification and Context for Keyword Selection

The selection of keywords-Embedded Systems, IoT, and Ai-was not arbitrary but reflects the current hardware-software co-design paradigm [27]. In the contemporary technological landscape, the "Internet of Things" acts as the nervous system of modern infrastructure, while "Embedded Systems" represent the physical body. The addition of "Artificial Intelligence" (specifically Machine Learning and Deep Learning) provides the "brain" or the decision-making capability [28].

The inclusion of terms like "Edge Computing" and "TinyML" in the query is particularly significant. These terms represent the cutting edge of the field, where the challenge lies in optimizing complex neural networks to run on low-power, memory-constrained microcontrollers [18]. This methodological focus allows the study to explore how researchers are tackling the "latency vs. accuracy" trade-off and the "energy efficiency" challenge [29]. By analyzing these specific keywords, the study can track the shift from "Cloud-centric AI" to "On-device Intelligence," which is essential for privacy-sensitive and real-time applications such as autonomous vehicles, smart healthcare, and industrial automation (Industry 4.0) [17].

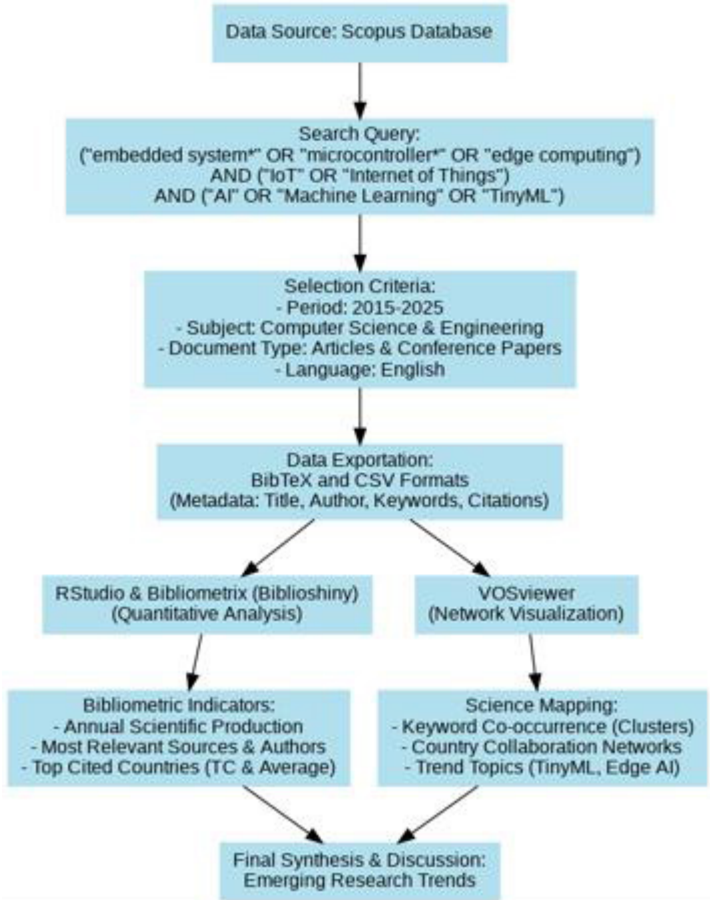

Figure.1 Methodological workflow of the bibliometric study

IV. RÉSULTATS

A. Main information of this study

The bibliometric indicators summarized in Table 1 reveal an extraordinary research dynamic and a rapid expansion of the scientific field linking embedded systems, IoT, and Artificial Intelligence between 2014 and 2026. Based on a corpus of 2,621 documents published across 528 distinct sources, the domain exhibits a staggering annual growth rate of 61.21% [30], signaling a massive technological pivot toward decentralized intelligence over the last decade. The extreme 'recency' of the research is further underscored by an average document age of only 2.97 years, confirming that the majority of scholarly contributions focus on cutting-edge breakthroughs such as TinyML and Edge AI. Despite the field's novelty, its intellectual impact is profound, as evidenced by a high average of 37.92 citations per document and a vast foundation of 207,847 cited references, indicating a research area anchored in rigorous theoretical frameworks. Socially, the data unveils a highly collaborative ecosystem: with an average of 4.5 co-authors per publication and an international co-authorship rate of 40.75%, it is evident that the complex challenges of optimizing AI algorithms for resource-constrained hardware demand a global and multidisciplinary synergy. These metrics ultimately validate that the fusion of hardware and cognitive software has become one of the most vibrant and high-impact research frontiers in contemporary computer science [30].

Figure 2 illustrates the temporal evolution of research output within the intersection of embedded systems, IoT, and Artificial Intelligence over a decade. The data reveals a clear and accelerating upward trajectory, which can be categorized into two distinct phases. From 2014 to 2017, the field remained in an embryonic stage, characterized by a marginal number of publications. However, a significant turning point occurred in 2018, followed by an exponential surge from 2020 onwards [31]. The production volume rose sharply from approximately 190 articles in 2020 to over 440 in 2023, representing more than a doubling of the research output in a span of only four years. This explosive growth underscores a major paradigm shift in the scientific community, likely fueled by the maturation of Edge AI and TinyML technologies, alongside the increasing global demand for autonomous and decentralized intelligent systems. The sustained momentum observed in the most recent years suggests that this convergence has transitioned from a niche academic topic to a cornerstone of modern industrial and computational research [32].

Tableau 1:
The main informations of this study bibliometric

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2014:2026
Sources (Journals, Books, etc)	528
Documents	2621
Annual Growth Rate %	61.21
Document Average Age	2.97
Average citations per doc	37.92
References	207847
DOCUMENT CONTENTS	
Keywords Plus (ID)	11630
Author's Keywords (DE)	5867
AUTHORS	
Authors	9370
Authors of single-authored docs	88
AUTHORS COLLABORATION	
Single-authored docs	89
Co-Authors per Doc	4.5
International co-authorships %	40.75
DOCUMENT TYPES	
Article	2621

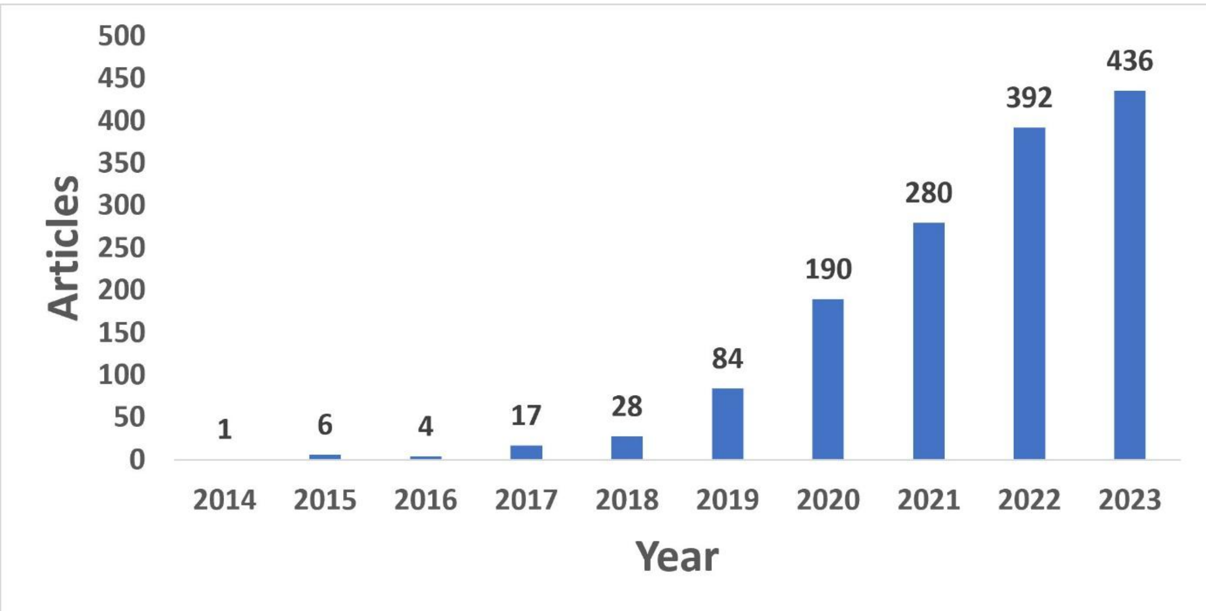

Figure.2 Evolution of the number of research articles per year.

B. The most productive journals

The bibliographic coupling of sources, illustrated in Figure 3, reveals the intellectual structure and thematic cohesion of the research field through a network of highly interconnected journals [33]. The map is characterized by the presence of a central hub, dominated by the IEEE Internet of Things Journal, which stands as the most influential venue for disseminating research on the convergence of IoT and intelligent systems. Surrounding this core, several thematic clusters emerge: a prominent yellow cluster composed of specialized IEEE Transactions (such as Wireless Communications, Mobile Computing, and Communications Surveys & Tutorials), which represents the network and connectivity foundation of the field; a green and red cluster featuring journals like Sensors and Computers & Electrical Engineering, highlighting the hardware-centric research focused on data acquisition and embedded computing; and a blue cluster anchored by IEEE Access, reflecting a multidisciplinary bridge for general engineering and rapid technological integration [34]. The high density of links between these nodes signifies a strong degree of intellectual overlap and cross-disciplinary citations, suggesting that the development of AI-driven embedded systems is a holistic endeavor that integrates communications, hardware design, and software intelligence [35]. Ultimately, this network confirms that the scientific discourse is primarily spearheaded by high-impact engineering societies, with a clear trajectory toward more integrated and sensor-rich IoT environments [36].

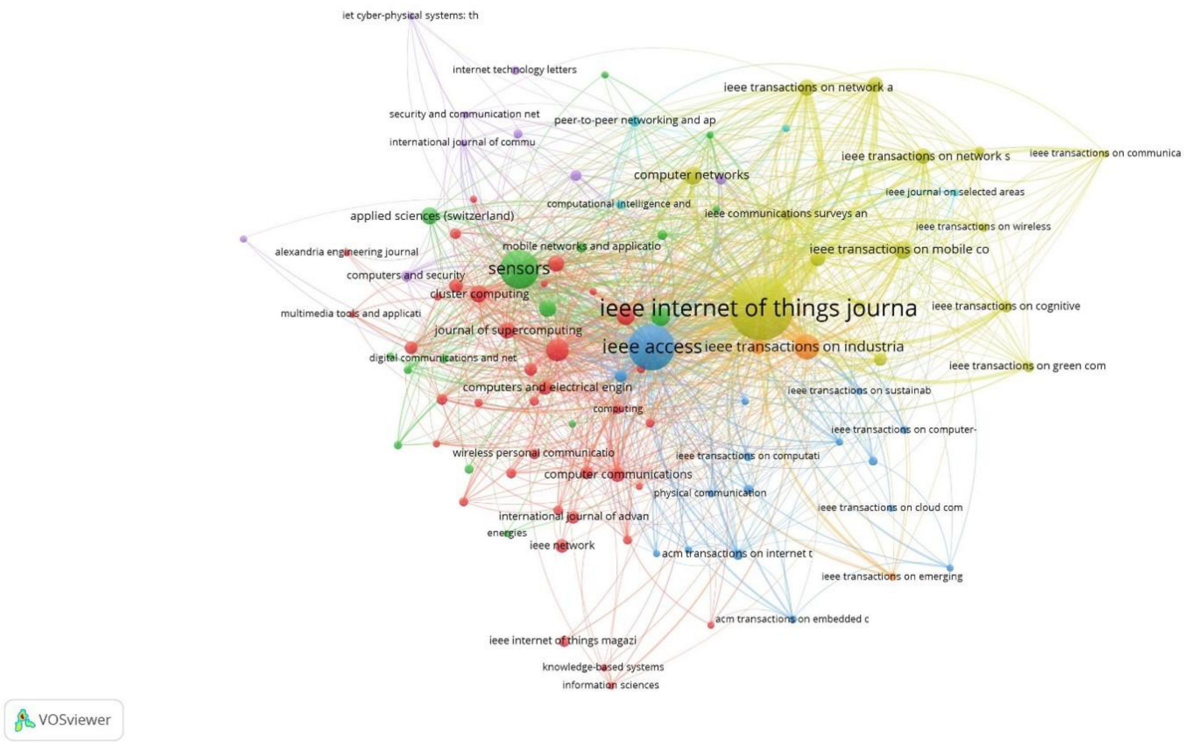

Figure.3 Bibliographic coupling network of the most influential journals in the field

The distribution of the most productive journals, as illustrated in Figure 4, highlights the primary publishing venues for research at the intersection of Embedded Systems, IoT, and Artificial Intelligence. The IEEE Internet of Things Journal stands out as the predominant leader with 387 documents, firmly establishing itself as the central hub for scholarly discourse in this domain. It is followed by IEEE Access (206 documents) and Sensors (146 documents), which reflects a clear preference among researchers for high-impact, multidisciplinary, and open-access platforms to disseminate their work [37].

The presence of specialized journals such as IEEE Transactions on Industrial Informatics (60) and Future Generation Computer Systems (50) further emphasizes the industrial and large-scale computational applications of these technologies [38]. Notably, the top 10 list is heavily dominated by IEEE publications, which account for half of the most relevant sources [39]. This dominance underlines the fact that the convergence of hardware intelligence and connectivity is a research field deeply rooted in professional engineering societies. The variety of sources-ranging from pure electronics (IEEE Transactions on Consumer Electronics) to network-centric journals

(Computer Networks)-demonstrates the multifaceted nature of the field, requiring a synthesis of hardware design, telecommunications, and advanced computing [40].

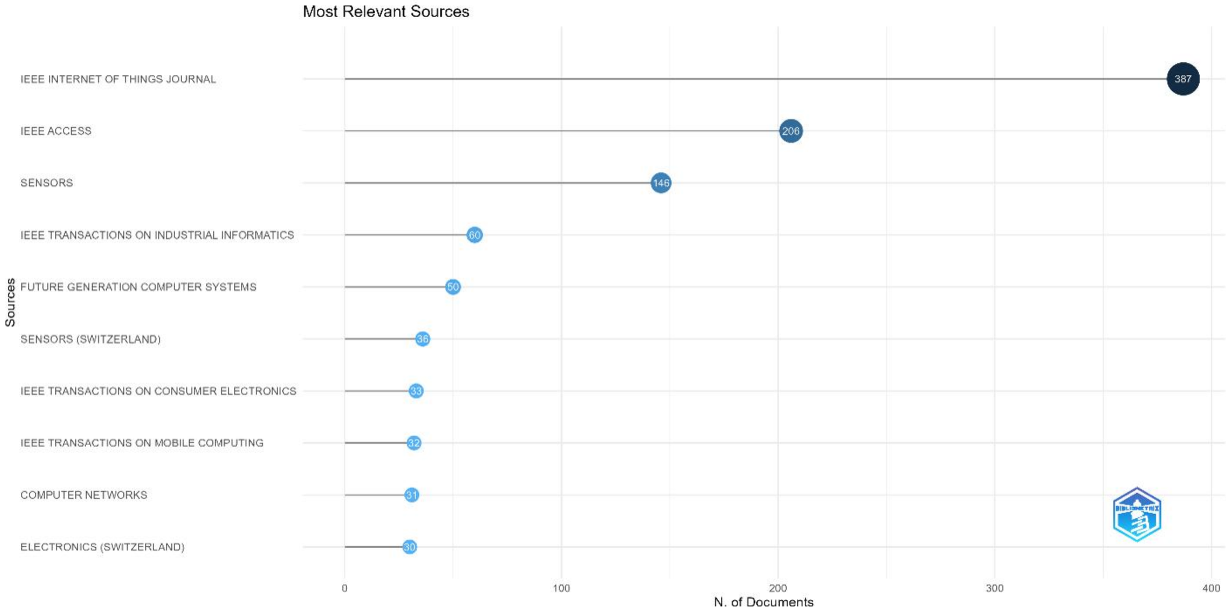

Figure.4 The most relevant sources

C. Analyse of the Authours

1. Network between co-Authours

The social structure of the research field is mapped in Figure 5, illustrating the collaborative networks between the most influential authors [41]. This co-authorship visualization, generated via VOSviewer, identifies the key 'gatekeepers' and research communities driving the integration of AI, IoT, and embedded systems [42]. The analysis reveals several prominent clusters, each centered around prolific scholars such as Mohsen Guizani, Dusit Niyato, Tian Wang, and Rajkumar Buyya. The size of the nodes indicates a high volume of scientific production and citation impact, while the density of the links between nodes reflects a robust and mature collaborative ecosystem [43]. The presence of multiple interconnected clusters suggests that research in this domain is rarely conducted in isolation; instead, it thrives on multi-disciplinary synergy between international research groups. For instance, the central position of authors like Guizani and Niyato underscores their role as primary bridges between different thematic areas, facilitating the exchange of knowledge across geographic and institutional boundaries. Ultimately, this network demonstrates that the advancement of intelligent embedded solutions is a collective global effort, characterized by strong scholarly ties and shared expertise [44].

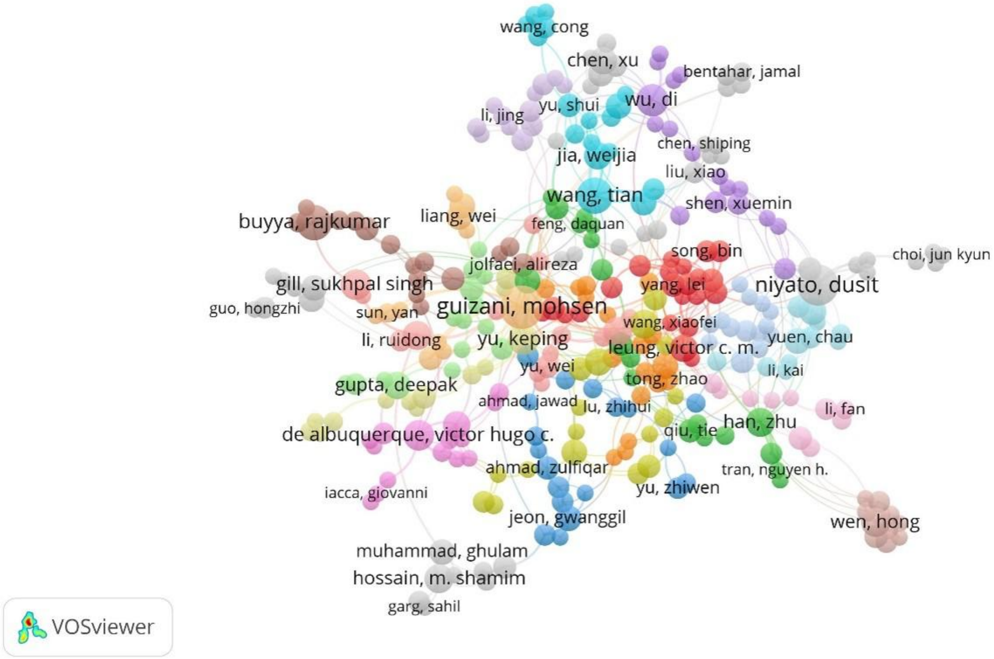

Figure.5 Network between the co-authours in this study

2. *Impact of authors on scientific output*

Table 2 provides a comparative analysis of the most influential researchers in the field, evaluated through three key bibliometric metrics: the h-index, Total Citations (TC), and the Number of Publications (NP). Mohsen Guizani emerges as the leading figure in terms of productivity and consistency, boasting the highest h-index (15) and the largest volume of publications (20) within the studied timeframe. Interestingly, while Rajkumar Buyya has a lower number of publications (13) compared to the top leaders, he has accumulated the highest scientific impact with 1,452 total citations, indicating that his contributions are considered seminal and highly influential by the global research community. Similarly, authors like Sukpal Singh Gill and Di Wu demonstrate a very high 'citation-to-paper' ratio, with over 1,200 citations for only 10 and 11 papers respectively [45]. The presence of scholars such as Dusit Niyato and Tian Wang, both maintaining a solid h-index of 12, further illustrates a group of elite experts whose work forms the intellectual backbone of the convergence between IoT, AI, and embedded systems. Collectively, these metrics highlight a research landscape driven by a small group of high-impact individuals whose scholarly output significantly shapes the technological trajectory of the domain [46].

Tableau 2:
Top 10 most influential authors based on h-index, Total Citations (TC), and Number of Publications (NP)

Author	h_index	TC	NP
GUIZANI MOHSEN	15	1184	20
NIYATO DUSIT	12	1120	18
WANG TIAN	12	882	14
BUYYA RAJKUMAR	9	1452	13
DE ALBUQUERQUE VICTOR HUGO C.	9	676	11
HOSSAIN M. SHAMIM	9	897	9
WEN HONG	9	655	9
GILL SUKHPAL SINGH	8	1237	10
RODRIGUES JOEL J. P. C.	8	309	9
WU DI	8	1234	11

3. The most cited documents worldwide

Table 3 identifies the intellectual landmarks of the research field by listing the top 10 most globally cited papers [47]. The data is analyzed through two distinct metrics: TC per Year, which measures the immediate resonance of a study, and Normalized TC, which provides a standardized comparison by accounting for the publication year. The article by Zhou Z. (2019), published in Proceedings of the IEEE, stands as the most influential work in terms of yearly impact, accumulating 258.88 citations per year. This suggests that Zhou's research provides a foundational framework for the convergence of AI and IoT that continues to be heavily referenced. Interestingly, the work of Ferrag M.A (2022) in IEEE Access exhibits the highest Normalized TC (19.05), despite being one of the most recent publications. This indicates an exceptionally rapid adoption and high relative impact of newer research, likely addressing urgent challenges in security or privacy within the Edge AI domain. Furthermore, the dominance of prestigious venues such as IEEE Network, IEEE Transactions on Industrial Informatics, and Future Generation Computer Systems confirms that the most impactful breakthroughs are concentrated in top-tier engineering journals. Collectively, these papers represent the 'core literature' that shapes current academic discourse and defines the technological trajectories of intelligent embedded systems [48].

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Tableau 3:
Top 10 most globally cited documents based on Total Citations (TC) per Year and Normalized TC

Paper	TC per Year	Normalized TC
ZHOU Z, 2019, PROC IEEE	258.88	14.18
LI H, 2018, IEEE NETWORK	166.44	9.18
HUANG L, 2020, IEEE TRANS MOB COMPUT	146.86	12.09
FERRAG MA, 2022, IEEE ACCESS	178.80	19.05
CHENG N, 2019, IEEE J SEL AREAS COMMUN	110.25	6.04
AHMED I, 2022, IEEE TRANS IND INF	153.40	16.34
MINERVA R, 2020, PROC IEEE	100.14	8.25
TULI S, 2020, FUTURE GENER COMPUT SYST	93.43	7.69
NGUYEN DC, 2021, IEEE INTERNET THINGS J	103.50	10.01
HATCHER WG, 2018, IEEE ACCESS	67.33	3.71

D. Keyword analysis

1. Co-occurrence of keywords

The mapping of keyword co-occurrences, illustrated in Figure 6, provides a comprehensive visualization of the intellectual core and the thematic evolution of the research field [49]. The network is anchored by two massive central nodes-'Internet of Things' and 'Artificial Intelligence-which serve as the primary conduits for all secondary research themes [50]. A detailed analysis of the clusters reveals four major research frontiers: first, a robust green cluster focused on network infrastructure and optimization, emphasizing 5G/6G connectivity, computation offloading, and quality of service; second, a significant blue cluster dedicated to cybersecurity and network security, highlighting the critical priority of protecting intelligent systems from intrusion and adversarial threats; third, a yellow and red cluster representing diverse application domains such as Industry 4.0, healthcare, and smart grids; and finally, a localized but crucial purple cluster featuring terms like 'TinyML', 'model compression', and 'FPGA', which signifies the technical shift toward executing complex AI algorithms on resource-constrained embedded hardware. The high density of links between these thematic groups demonstrates that the field is moving away from isolated technical silos toward a holistic paradigm where connectivity, security, and decentralized intelligence converge to enable the next generation of autonomous cyber-physical systems [51].

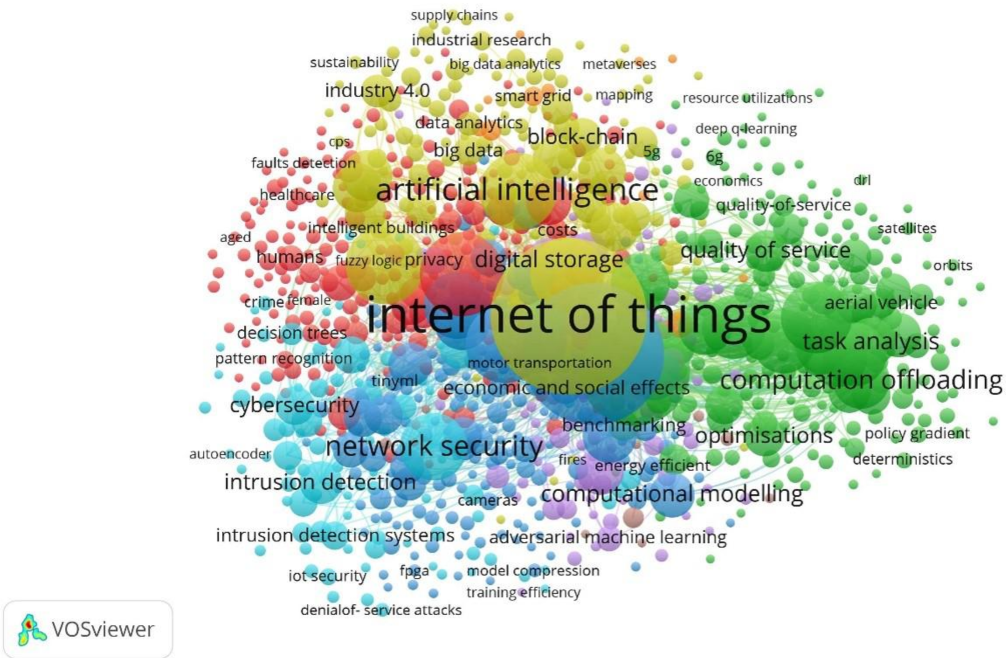

Figure.6 Co-occurence about the keywords in this study

2. Current topics

The chronological evolution of research themes, illustrated in Figure 7, reveals a significant paradigm shift in the scientific discourse over the last decade [52]. The analysis identifies three distinct phases of thematic development. In the early stage (2016-2019), the research was foundational, focused on sensors, cyber-physical systems (CPS), and monitoring, with a heavy reliance on cloud computing for data processing [53]. Between 2020 and 2023, the field entered a period of 'technological integration,' characterized by a massive surge in frequency for terms such as Internet of Things (IoT), Deep Learning, and Embedded Systems, which act as the central pillars of the dataset. Most notably, the data from 2024 to 2026 highlights the emergence of the current research frontier: a transition from centralized to localized intelligence [54]. Recent trends are dominated by edge computing, edge detection, and learning systems, reflecting the 'Edge AI' revolution. Furthermore, there is a clear and growing emphasis on non-functional requirements such as data privacy, computer privacy, network security, and green computing. This trajectory demonstrates that the field has matured beyond simple connectivity; the current focus is now on developing intelligent, autonomous systems that are not only high-performing at the hardware level but also energy-efficient and secure by design [55].

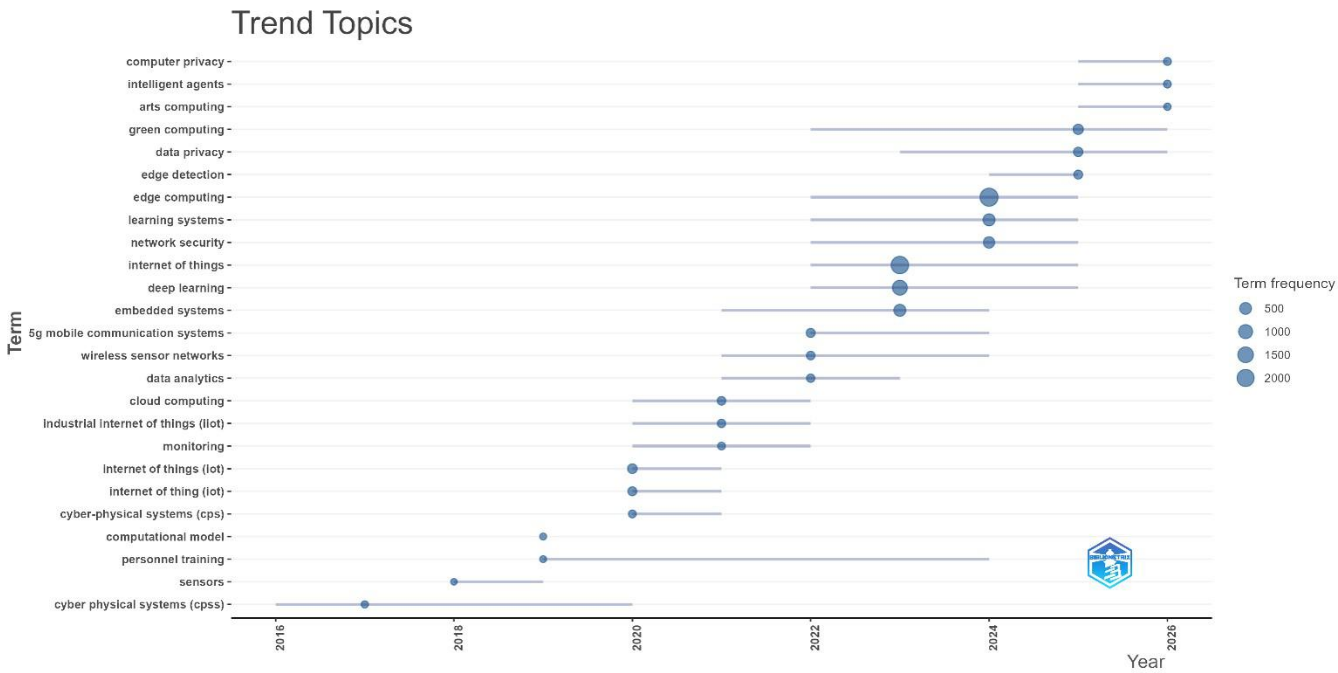

Figure.7 Evolution of trend topics based on author keywords (2016–2026)

E. Countries

1. Co-occurrence network between countries

The image presents a comprehensive bibliometric analysis of international scientific collaboration, divided into two complementary visualizations [56]. Panel B displays a network map generated by VOSviewer (Figure 8), where countries are represented by nodes [57]. The size of each node reflects the volume of scientific publications or the total link strength of a country, identifying China and the United States as the most influential "hubs" in this research field. The different colors represent distinct clusters of collaboration, such as a European cluster (red/pink), an Asian-Pacific cluster (orange), and a South Asian/Middle Eastern cluster (green). The density of lines between these nodes illustrates the intensity of co-authorship links, showing that while regional partnerships are strong, there is significant cross-continental cooperation [58].

Panel A complements the network data by projecting these relationships onto a geographical world map. The intensity of the blue shading (choropleth map) indicates the research productivity of each nation, with the darkest regions corresponding to the highest output, notably in North America and East Asia [59]. The superimposed brown lines map the physical flow of knowledge across the globe, highlighting major collaboration corridors between the US, Europe, and Asia. Together, these visualizations demonstrate a highly globalized research landscape where scientific progress is driven by a complex, interconnected web of international partnerships, dominated by the leadership of the United States and China [60].

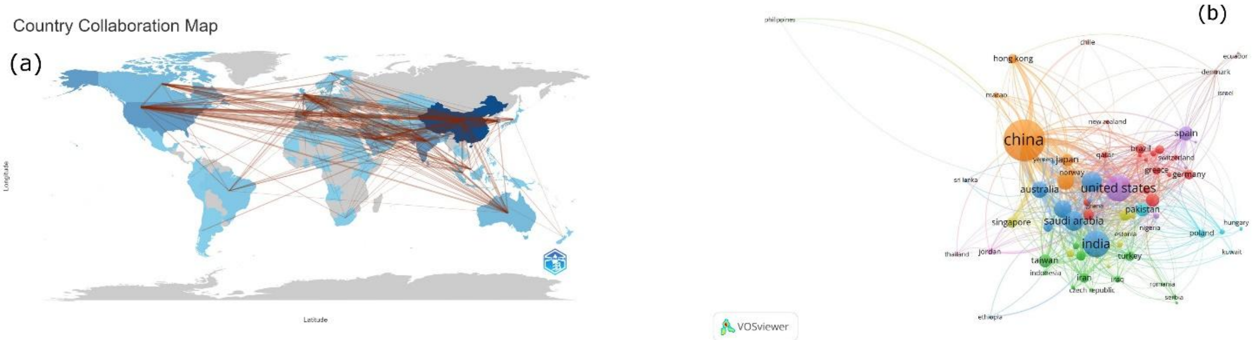

Figure.8 International Scientific Cooperation Landscape: (A) Bibliometric Network Analysis of Co-authorship and (B) Geospatial Distribution of Global Collaborations

2. The most frequently cited countries

The table 4 provides a bibliometric analysis of the top ten countries in a specific research field, comparing their Total Citations (TC) against their Average Article Citations. China clearly dominates the quantitative aspect of the data with a massive 36,631 total citations, far surpassing the United States (7,881) and India (5,590), which hold the second and third positions respectively. This suggests that China has an exceptionally high volume of research output or a few extremely high-impact papers that drive the total count [61].

However, when evaluating the scientific impact per publication, the ranking shifts significantly. Australia leads the group with the highest average of 74.80 citations per article, followed by the United Kingdom (57.90) and the United States (49.90) [62]. This indicates that while countries like China and India (which has the lowest average at 21.50) produce a large quantity of research, countries like Australia and the UK produce papers that, on average, carry more scientific weight or influence. In summary, the data illustrates a clear distinction between quantitative dominance (led by China) and qualitative impact per paper (led by Australia and the UK) [63].

Tableau 4:
Bibliometric Performance Metrics of the Top 10 Countries by Total and Average Citations

Country	TC	Average Article Citations
CHINA	36631	42.00
USA	7881	49.90
INDIA	5590	21.50
UNITED KINGDOM	4628	57.90
KOREA	3715	31.50
AUSTRALIA	3592	74.80
SAUDI ARABIA	2618	38.50
ITALY	2466	37.90
SPAIN	2027	25.70
CANADA	1957	33.70

V. DISCUSSION

The findings of this bibliometric analysis underscore a monumental expansion of the scholarly landscape at the intersection of AI, IoT, and embedded systems, characterized by an extraordinary annual growth rate of 61.21% that signals a definitive shift toward the era of Edge Intelligence. This trajectory validates the core premise of a fundamental paradigm shift where the locus of data processing is migrating from centralized cloud infrastructures to the network's periphery to mitigate critical bottlenecks related to latency and data sovereignty, thereby providing strong empirical support for Hypothesis 1, which links decentralized processing to the broader adoption of localized cognition. Furthermore, the thematic dominance of TinyML, FPGA optimization, and model compression within the identified research clusters highlights a sophisticated movement toward hardware-software co-design; this development aligns with Hypothesis 2 by demonstrating that the successful deployment of embedded AI systems is strictly contingent upon overcoming the "latency vs. accuracy" trade-off through technical breakthroughs at the microcontroller level. Beyond mere computational performance, the recent surge in keywords such as green computing, network security, and data privacy between 2024 and 2026 indicates a maturation of the field, where the long-term sustainability of autonomous cyber-physical systems—as posited in Hypothesis 3—is increasingly dependent on non-functional requirements and ethical design frameworks. Geopolitically, the data reveals a nuanced dichotomy where China leads in sheer publication volume, while nations like Australia, the UK, and the USA maintain a significantly higher qualitative impact per document, suggesting a complex global ecosystem where Asian hubs drive large-scale implementation while Western institutions often act as conceptual gatekeepers. Ultimately, this convergence has transcended its status as a niche academic topic to become the institutionalized backbone of Industry 4.0, necessitating a holistic synthesis of connectivity, hardware efficiency, and intelligent algorithms to enable the next generation of truly autonomous and secure intelligent systems.

VI. CONCLUSION

This bibliometric study has provided a comprehensive mapping of the evolution and convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and Embedded Systems between 2015 and 2025. The results reveal a field in a state of rapid expansion, characterized by a staggering annual growth rate of 61.21%, signaling a major global pivot toward the era of Edge Intelligence. The analysis highlights a scientific landscape dominated quantitatively by China, while nations such as Australia, the United Kingdom, and the United States lead in terms of qualitative impact per publication. The intellectual framework of the field is deeply rooted in professional engineering societies, with the IEEE Internet of Things Journal serving as the primary hub for disseminating high-impact research. This collaborative ecosystem is increasingly global, with a high rate of international co-authorship reflecting the multidisciplinary nature of optimizing AI for resource-constrained hardware. Thematic mapping confirms a significant paradigm shift: research has transitioned from cloud-centric architectures to decentralized, on-device intelligence. The emergence of TinyML, FPGA-based optimization, and 5G/6G connectivity demonstrates that the current challenge lies in executing complex neural networks on low-power devices. Furthermore, the growing emphasis on data privacy, network security, and green computing defines the current research frontier, where performance must be balanced with energy efficiency and ethical considerations.

In conclusion, the synergy between hardware design and cognitive software is no longer a niche academic topic but has become the cornerstone of Industry 4.0 and future autonomous systems. Future research must continue to address the "latency vs. accuracy" trade-off and develop robust, secure frameworks to support the widespread deployment of intelligent cyber-physical systems. This study serves as a roadmap for researchers and stakeholders to navigate the complex and rapidly evolving landscape of intelligent embedded solutions.

Author Contributions: *Mohamed NOUAYTI:* Conceptualization, Methodology, Writing - Original Draft, Data Curation. *Anass AYNAOU:* Software, Investigation, Formal analysis, Writing - Review & Editing. *Nordine NOUAYTI:* Investigation, Data Curation, Validation. *Younes ADNANI:* Conceptualization, Supervision, Writing - Review & Editing.
All authors have read and agreed to the published version of the manuscript.

Funding: *This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.*

Acknowledgments: The authors would like to express their gratitude to the Applied Sciences Laboratory at Abdelmalek Essaadi University and the Department of Business Administration at Politeknik Negeri Madiun for providing the academic environment and resources necessary to carry out this study.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: The datasets analyzed during the current study were retrieved from the Scopus database. The processed bibliometric data and generated maps are available from the corresponding author upon reasonable request.

Informed Consent: There were no human subjects.

Institutional Review Board Statement: Not applicable.

Animal Subjects: There were no animal subjects.

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