

The Evolution in Human Activity Recognition and Artificial Intelligence – A Decade of iWOAR

Ruben Schlonsak^{1,2}, Marco Gabrecht^{1,2}, and Denys J.C. Matthies^{1,2}

¹ Technical University of Applied Sciences Lübeck, Germany
<firstname>.<lastname>@th-luebeck.de

² Fraunhofer IMTE, Lübeck, Germany

Abstract. This paper reviews the decade-long journey of the International Workshop on Sensor-based Activity Recognition (iWOAR), tracing its evolution from a regional workshop in Rostock, Germany, into a prominent international forum. The iWOAR has served as a critical platform for discussing and advancing human activity recognition (HAR) through pervasive and wearable computing. This paper provides a comprehensive meta-analysis of the iWOAR's publication history, exploring shifting research trends, such as the transition from classical machine learning to deep learning, and analyses key community metrics. By reflecting on past milestones, the paper outlines future directions for the research field as it enters its second decade.

Keywords: iWOAR · Conference · Human Activity Recognition · AI · Machine Learning

1 Introduction

The field of Human Activity Recognition (HAR) has undergone a rapid transformation over the past decade, evolving from basic motion detection using hand-crafted features to sophisticated, AI-driven systems capable of understanding complex human behaviors and physiological states. This trajectory is also clearly reflected in the history of the iWOAR conference beginning in 2014 until today.

In its foundational years (2014–2016), iWOAR emerged alongside the global "Quantified Self" movement, which was driven by the sudden availability of inexpensive MEMS-based sensors in consumer smartphones and early wearables. During this era, the workshop focused on the fundamental feasibility of using inertial sensors to track states like sleep, stress, and any movement activities. This mirrored the broader HAR field's shift from laboratory settings to real-world data collection. Technologically, this was the period of manual feature engineering and conventional machine learning, where the research priority was often in proving that consumer-grade accelerometers could reliably monitor clinical conditions, such as tremor recognition and be useful for occupational health.

As the conference matured, it transitioned from hardware exploration to complex algorithmic modeling, reflecting the "Deep Learning explosion" that

revolutionized the entire AI landscape. The papers presented during this period increasingly utilized Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which automated the extraction of patterns from raw sensor data. This allowed the conference to align with the global Industry 4.0 trend, prioritizing assisted production and manual order-picking workflows. This matched a general shift in the HAR community from recognizing simple ambulatory activities (like walking or sitting) to tracking complex tasks and extracting physiological biomarkers, such as heart and respiration rate.

By 2026, iWOAR has matured into a forum for "Human-Centered Intelligence" and multimodal sensing, mirroring the current peak of AI research. The scope has broadened beyond body-worn hardware to include ambient, device-free sensing and niche applications like animal welfare, reflecting a global move toward Pervasive Computing where intelligence is integrated into the environment itself. Technologically, the workshop now also highlights state-of-the-art architectures like Transformers and real-time vision analysis. Interestingly, the conference now also emphasizes on the ethical pillars of modern AI—systems, mental wellbeing, and energy efficiency—reflecting the industry’s shift toward responsible and sustainable AI technology.

1.1 Mission Statement

The International Workshop on Sensor-Based Activity Recognition and Artificial Intelligence (iWOAR) aims to provide a conference-like forum for researchers and practitioners to share and discuss advances in sensor-based activity and behavior recognition using artificial intelligence and related technologies. The workshop brings together scientists, developers, and practitioners from diverse academic and industrial backgrounds to present high-quality contributions that advance methodologies, systems, and applications in human and even animal activity recognition with wearable and pervasive sensing technologies. iWOAR fosters exchange of scientific results, best practices, and emerging trends in topics including activity and wellbeing detection, affective and real-time computing, context-awareness, assistive technologies, and ethical considerations in sensing applications. Accepted contributions undergo peer review and are disseminated in peer-reviewed proceedings, promoting rigorous research and community building in the field.

1.2 History

The first iWOAR, formerly known as WOAR³ was published in 2014 at the Fraunhofer Verlag. WOAR 2014 was held in Rostock with the aim of bringing together the Fraunhofer IGD and the University of Rostock and other scientific players, fostering a deeper collaboration. This was the motivation following the general chair Bodo Urban. Back then, the workshop was held at the Fraunhofer

³ <https://publica.fraunhofer.de/entities/publication/5335f599-f8c7-4e80-aa19-a83e125228cc>

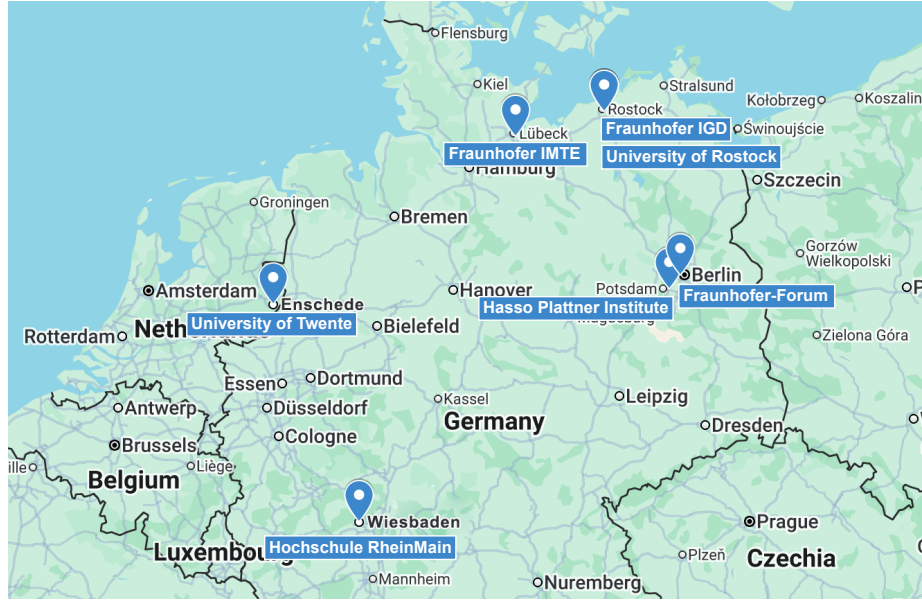


Fig. 1: Locations the iWOAR was hosted at throughout the past decade.

IGD, which was more a local event. One year later Denys Matthies drove the idea forward to expand the event to an international conference adding the ‘i’ to the acronym resulting in iWOAR – international Workshop on Sensor-based Activity Recognition and Interaction⁴, which is now published by ACM. Also the program committee was expanded to be more international. Renown professors, such as Paul Lukowicz⁵, Antonio Krüger⁶, Christian Haubelt⁷, Jesse Hoey⁸, Albrecht Schmidt⁹, Alex Mihailidis¹⁰, Ian Craddock¹¹, Fillia Makedon¹², Kristof van Laerhoven¹³, Björn Eskofier¹⁴, Niels Henze¹⁵, Thomas Plötz¹⁶, Özlem Durmaz Incel¹⁷, Michael Beigl¹⁸, and Kate Farrahi¹⁹ gave inspiring keynote talks

⁴ <https://iwoar.org/2015>

⁵ <https://scholar.google.com/citations?user=1FIyc9kAAAAJ>

⁶ <https://scholar.google.com/citations?user=IJb7hWYAAAAJ>

⁷ <https://scholar.google.com/citations?user=splR7LcAAAAJ>

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¹⁸ <https://scholar.google.com/citations?user=9-WU64IAAAAAJ>

¹⁹ https://scholar.google.com/citations?user=c_E3E4kAAAAJ

since then. During the COVID-19 pandemic, iWOAR was not held for two years in a row, as the conference has traditionally relied on in-person participation. Participants particularly valued the opportunity for direct physical presence, informal exchanges, and open discussions in an accessible and uncomplicated setting. Throughout the first few years the iWOAR was usually hosted at the Fraunhofer IGD Rostock and the University of Rostock. After the death of our appreciated professor Bodo Urban, who wanted to keep iWOAR close to Rostock, the steering committee decided to bring iWOAR to different locations. Meanwhile it also took place at the Fraunhofer-Forum in Berlin, later at the Fraunhofer IMTE Lübeck, Hasso Plattner Institute Potsdam, and in 2025 it was held the first time outside of Germany at the University of Twente in Enschede, Netherlands (see Figure 1). Due to dis-alignments with the publisher's new licensing policies, iWOAR has been published via Springer LNCS since 2024.

1.3 Voices of iWOAR

Numerous individuals have repeatedly contributed to the organization of the event. We would like to share their motivations and thoughts with you:



Denys J.C. Matthies: *"I have been involved with iWOAR very frequently since 2015. My motivation for organizing the conference comes from a passion for research in the field of sensor-based activity recognition and HCI. My initial goal has been to use the event as a vehicle to connect international researchers from all over the world. While many other conferences share this mission, iWOAR is particularly small, which allows me to personally get in touch with every participant. Over*

the years, I have met both young, ambitious researchers and established scientists. Even lasting friendships arose throughout the years! I greatly enjoy the relaxed atmosphere, unforced conversations, and of course the social events. I believe iWOAR is especially well-suited for emerging research, supporting younger scientists while giving them the chance to contribute to shaping the program and the community."



Gerald Bieber: *"I really enjoy iWOAR. The workshop is always engaging and filled with interesting people. It provides great opportunities to meet fellow researchers, exchange ideas, and establish connections for future proposals or projects. Furthermore, the contributions are often unique, featuring new ideas, concepts, or early-stage prototypes. These innovations are sometimes more interesting than the large-scale studies or continuations of existing research often found at other conferences."*



Arjan Kuijper: *I have to confess: I missed the first iWOAR. I apologize for that! I started with number 2, but then I did it substantially – with papers authored by one of the current conference chairs and one of the invited speakers! That was the starting point of long involvement in iWOAR, as (co-)author and organizer. The reason for that is quite easy: iWOAR is a nice community where one still has time to discuss research with each other without the need to hurry to another session. It's also cosy in the sense that you have time to see, meet and get to know other participants during the conference and especially during social event which is truly social. This is in big contrast to so many other conferences where you get lost in the crowd. So iWOAR combines the best of the scientific and the social worlds. That motivated me to be active in the community and contribute to it for so many years. Still counting!x*

2 Statistics

Until end of 2025, a total of 160 papers and posters have been published accumulated across all iWOAR proceedings²⁰. To analyze the scientific impact of these publications, we collected citation data from two complementary sources: Google Scholar, which provides the broadest coverage including theses, technical reports, and non-indexed venues, and OpenAlex, an open bibliometric database that covers peer-reviewed literature. Of the 160 papers, 154 are indexed in OpenAlex (the 6 Fraunhofer Verlag papers from 2014 are not), while Google Scholar provides citation data for all 160. Author metadata (affiliations, country codes) was obtained from OpenAlex profiles and supplemented with author names extracted from the original BibTeX entries where no OpenAlex record exists. Based on Google Scholar citation data, the following scientific metrics emerge (as of February 2026):

- **h-index: 19** (At least 19 papers have each been cited at least 19 times)
- **i10-index: 38** (Number of publications with at least 10 citations)
- **Total citations: 1,426** (Accumulated across all ten volumes)
- **Average citations per paper: ~8.9**

²⁰ [112, 122, 55, 18, 15, 1, 153, 56, 39, 26, 3, 83, 12, 52, 145, 53, 95, 49, 117, 7, 131, 20, 93, 27, 80, 160, 58, 132, 154, 72, 37, 121, 54, 23, 141, 48, 143, 155, 106, 90, 100, 86, 35, 148, 31, 118, 81, 4, 149, 62, 16, 85, 103, 46, 101, 92, 107, 68, 57, 36, 142, 61, 77, 40, 126, 144, 123, 127, 33, 73, 140, 24, 105, 76, 66, 115, 84, 63, 109, 65, 99, 97, 147, 88, 21, 10, 75, 47, 135, 139, 136, 8, 34, 151, 60, 79, 130, 30, 41, 32, 50, 157, 51, 64, 42, 98, 150, 6, 11, 133, 111, 137, 78, 114, 59, 82, 94, 124, 29, 45, 43, 67, 108, 129, 158, 19, 146, 70, 5, 38, 69, 125, 44, 89, 159, 120, 102, 156, 22, 91, 116, 17, 28, 134, 2, 110, 128, 13, 14, 119, 113, 87, 104, 138, 96, 25, 152, 71, 74, 9]

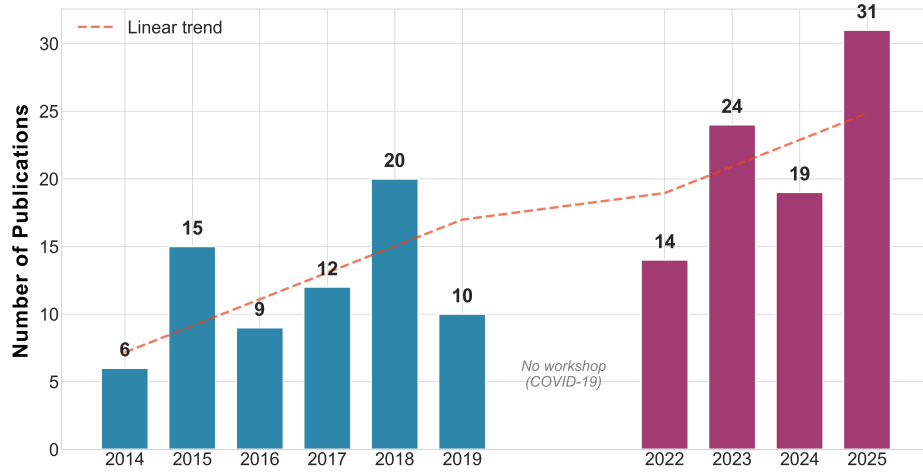


Fig. 2: iWOAR publications per year (2014–2025). The dashed line indicates a linear trend, the gap corresponds to years without a workshop (COVID-19 period). The publications include full papers and short / poster papers.

2.1 Connecting the dots: Venues, Submissions, Acceptance Rates and Publishers

Over the past few years, iWOAR has seen growing interest within the research community, as evidenced by the publication trends shown in Table 1. While the data indicated certain cyclic patterns, these are closely linked to specific organizational shifts, which we are going to explain now. A significant milestone occurred in 2015, when iWOAR transitioned to ACM as its publisher. This move increased international visibility and initially boosted the venue’s relevance. In the subsequent years, however, the workshop was primarily hosted by the Fraunhofer IGD and the University of Rostock. This focus on a single location led to the perception of iWOAR as a more localized event, which may have limited its appeal to international participants. A notable exception occurred in 2018, where a peak in engagement coincided with the move to the Fraunhofer-Forum in Berlin. Following a two-year hiatus due to the COVID-19 pandemic, the workshop was relaunched in Rostock before adopting a more mobile strategy. Subsequent editions in Lübeck and Potsdam, culminating in the first international venue in Enschede (2025), have led to record-high submission numbers and highly competitive acceptance rates (*see Figure 1*). These trends

Table 1: Acceptance Rates of full papers published at iWOAR (2014–2025).

iWOAR	1st 2014	2nd 2015	3rd 2016	4th 2017	5th 2018	6th 2019	7th 2022	8th 2023	9th 2024	10th 2025
Acceptance Rate:	86%	68%	60%	63%	54%	91%	82%	40%	68%	45%

clearly underscore the community’s preference for rotating the workshop across diverse and internationally accessible locations.

The second publisher transition in 2024, from ACM to Springer, has not yet resulted in a discernible impact on publication trends. This strategic shift was necessitated by a change in ACM’s publishing model, which placed considerable pressure on organizers to ensure that publishing institutions entered into comprehensive institutional agreements. Under these new terms, authors from institutions without an active ACM Open Access agreement were subject to an individual article processing charge of USD 1,000, payable in addition to the standard conference registration fee. Furthermore, authors who failed to cover these additional processing fees in the past are placed on a black list, which conference organizers are compelled to monitor, potentially leading to the exclusion of their research from iWOAR. Such practices stand in direct opposition to the core principles of iWOAR, which is envisioned as an inclusive, affordable, non-profit venue "by researchers for researchers." The steering committee found ACM’s hurdles for researchers unsustainable and inconsistent with the community values, therefore, a change of publisher became inevitable.

3 Authors & Community

3.1 Community Growth and Author Retention

Over the past decade, a total of 470 authors have contributed to the iWOAR proceedings. Figure 3 shows the number of new and returning authors per conference year. Each edition brings a substantial influx of first-time contributors: from 14 authors at the inaugural WOAR 2014 to 113 unique authors at iWOAR 2025.

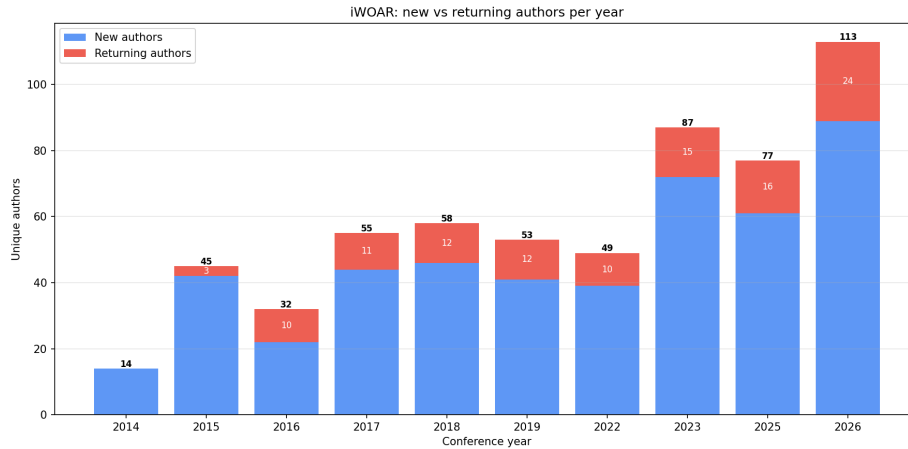


Fig. 3: New authors versus returning authors per conference year. Returning authors are those who have contributed to at least one prior edition. The return rate has stabilized around 20% since 2016.

Across all editions, 409 authors (87%) have contributed to exactly one edition, while 61 authors (13%) have returned for two or more years. The return rate per edition has remained remarkably stable at approximately 20% since 2016, indicating a healthy balance between community continuity and the regular infusion of new perspectives.

The most prolific returning authors span the entire history of the workshop. Gerald Bieber has contributed to 9 out of 10 editions, making him the most consistent participant. Denys J.C. Matthies and Thomas Kirste each appeared at 7 editions, followed by Kristof Van Laerhoven (6 editions), and Arjan Kuijper and Marian Haescher (5 editions each). These returning authors serve as institutional memory and provide continuity in the review process, topic evolution, and community building.

3.2 Prolific Authors and Citation Impact

Table 2 lists the most prolific iWOAR authors ranked by number of publications, revealing two distinct paths to influence: sustained productivity and high-impact contributions. In this ranking, Gerald Bieber leads with 17 papers across 9 editions, making him the most consistent contributor. Denys J.C. Matthies (16 papers) and Kristof Van Laerhoven (15 papers) follow. Notably, publication count and citation impact do not always correlate: while Matthies ranks second in productivity, his papers accumulate the highest total citations (260 on Google Scholar). Bodo Urban, with only 6 papers, ranks among the most-cited authors due to his involvement in the foundational 2014 proceedings and early high-impact contributions.

Table 2: Top 10 iWOAR authors by number of publications. These numbers reflect the total citation counts from Google Scholar (*GS*) and OpenAlex (*OA*).

Rank	Author	Articles	GS	OA	Editions
1	Gerald Bieber	17	78	87	9
2	Denys J.C. Matthies	16	260	208	7
3	Kristof Van Laerhoven	15	172	125	6
4	Thomas Kirste	10	75	42	7
5	Marian Haescher	7	87	85	5
6	Arjan Kuijper	7	109	90	5
7	Bert Arnrich	7	21	14	4
8	Ruben Schlonsak	7	9	2	4
9	Marcin Grzegorzec	6	55	35	3
10	Bodo Urban	6	252	155	4

Figure 4 compares total citations per conference year between Google Scholar and OpenAlex. Scholar consistently reports higher counts (1,426 total vs. 955 on OpenAlex), reflecting its broader coverage of finding citations that stem from theses, technical reports, and non-indexed venues, next to research papers. The

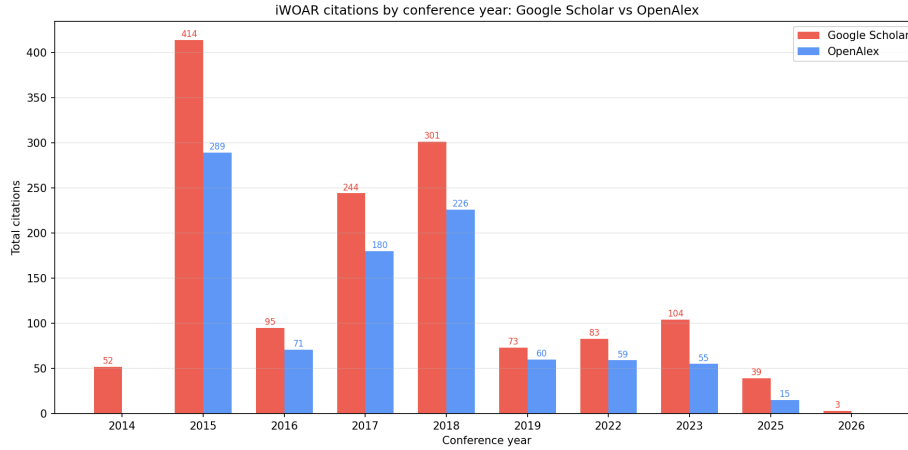


Fig. 4: Total citations per conference year according to Google Scholar (red) and OpenAlex (blue). Scholar consistently reports higher counts, with the gap most pronounced for early, high-impact cohorts.

2014 cohort shows Scholar citations exclusively, as these papers (published by Fraunhofer Verlag) are not indexed in OpenAlex.

3.3 Citation Maturity

Figure 5 presents the 20 most-cited iWOAR papers with citation counts from both Google Scholar and OpenAlex. The highest-cited paper is *Deep Neural Network based Human Activity Recognition for the Order Picking Process* [54] with 123 Scholar citations, followed by *Exploring Vibrotactile Feedback on the Body and Foot* [95] (118), *Human Activity Recognition Using Temporal Convolutional Network* [103] (75), and *A Study on Measuring Heart- and Respiration-Rate via Wrist-Worn Accelerometer-based Seismocardiography* [56] (71). Further notable contributions include *eRing* [145] (66), *Using Activity Recognition for Assembly Process Tracking* [1] (50), and *Using Wrist-Worn Activity Recognition for Basketball Game Analysis* [61] (48). The top 10 papers all originate from the 2014–2018 period, reflecting both citation maturity and the foundational nature of these contributions. Thematically, the most-cited works are not solely defined by AI advancements but also by quintessential HCI topics and tangible engineering artifacts—from IMU-based gloves for sign language [100] to electric-field rings [145]—reinforcing iWOAR’s dual identity as a venue for both algorithmic innovation and human-centered engineering.

Citation accumulation for iWOAR papers aligns with typical computer science trends, where publications accumulate most citations within 3–5 years. Consequently, older cohorts lead in citations. Specifically the 2015 cohort (averaging 27.6 Scholar / 19.3 OpenAlex citations) is followed by the edition of 2017, while papers from 2022 onward remain in their early citation windows.

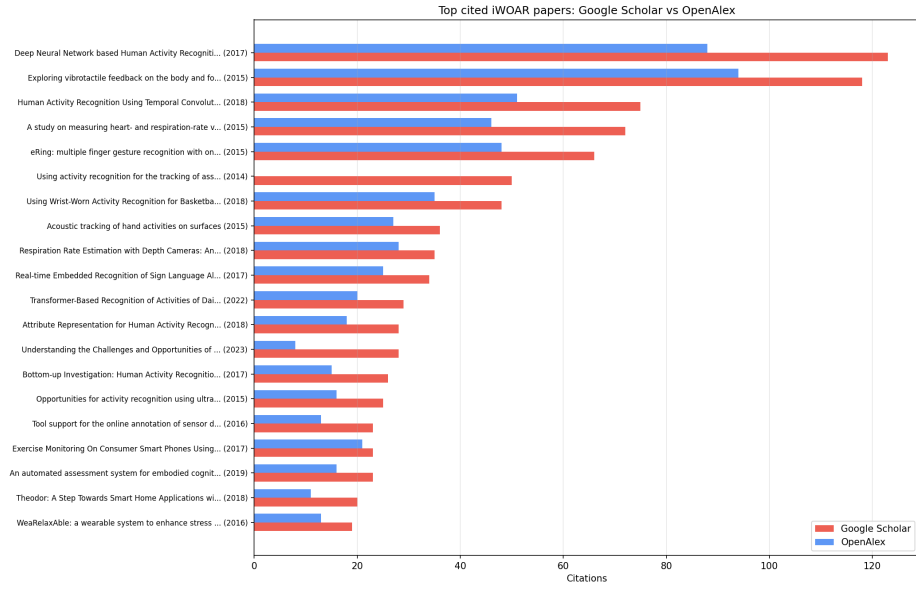


Fig. 5: Top 20 most-cited iWOAR papers. Red bars indicate Google Scholar counts, blue bars OpenAlex counts. The discrepancy between sources is consistent across all highly-cited papers.

3.4 Authors and Collaboration Patterns

Figure 6–left shows the distribution of authors by their number of iWOAR publications. The distribution follows a characteristic long-tail pattern: 393 authors (83.6%) have published exactly one paper, 56 authors (11.9%) have 2–3 papers, 13 authors (2.8%) have 4–6 papers, and only 8 authors (1.7%) have contributed 7 or more papers. This pattern is typical for specialized workshops and mir-

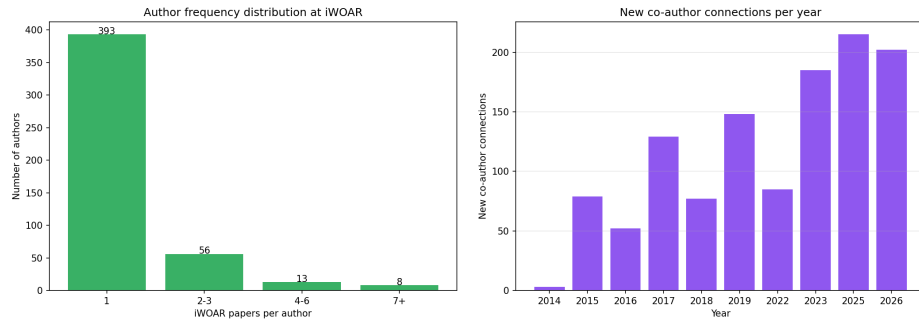


Fig. 6: Left: Distribution of authors by number of iWOAR publications. The long-tail distribution is characteristic of specialized academic venues. Right: Growth of the co-authorship network over time, showing the number of new unique collaboration pairs introduced at each edition.

rors broader bibliometric distributions observed across computer science venues, where a small core of highly productive authors coexists with a large periphery of occasional contributors.

The average number of authors per paper has increased from 2.8 in 2014 to values between 4 and 6 in recent editions, reflecting a broader trend toward larger, interdisciplinary research teams. Figure 6–right tracks the cumulative growth of unique co-authorship connections. Starting from 3 unique collaboration pairs in 2014, the network has expanded to over 1,175 unique edges by 2025, with each edition contributing between 50 and 215 new connections.

3.5 Internal Citation Network

Utilizing science principles akin to the "Eigenfactor"-metric, this section explores iWOAR’s internal citation network to uncover the structural topology and foundational papers that drive the workshop’s community. To quantify this, we retrieved 154 OpenAlex-indexed iWOAR papers and identified citations pointing to other papers within the same proceedings. Table 3 summarizes the results.

Table 3: iWOAR internal citation statistics. Papers citing iWOAR refers to papers that include at least one reference to another iWOAR publication.

Metric	Value
Papers analyzed (with OpenAlex data)	154
Papers citing at least one iWOAR paper	28 (18.2%)
Total internal citation links	42
Average internal refs per citing paper	1.5

Figure 7 provides two complementary views. The left panel shows the number of internal citation links per conference year alongside the percentage of papers that cite iWOAR.

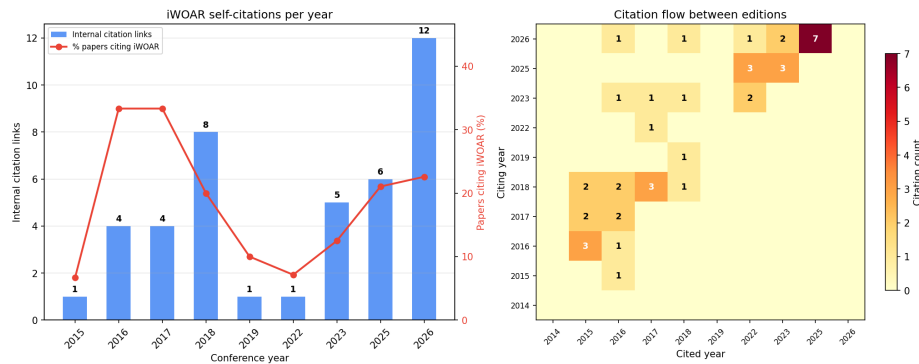


Fig. 7: Internal citation analysis. Left: number of iWOAR-to-iWOAR citation links (bars) and percentage of papers citing prior iWOAR work (line) per edition. Right: citation-flow heatmap showing how each edition references earlier ones.

that reference prior iWOAR work. While early editions show modest internal referencing (1–4 links), a clear upward trend emerges from 2023 onward, culminating in 12 internal links at iWOAR 2025. This suggests a maturing community that increasingly builds upon its own body of work. The right panel presents a citation-flow heatmap between editions. The strongest flows are directed from the 2025 edition toward the 2024 (7 links) and 2023 (3 links) cohorts, indicating that recent work frequently references the immediately preceding editions. The 2018 edition is notable for drawing references from the broadest range of prior years (2015–2018), reflecting its position as the largest pre-pandemic edition.

The most frequently cited paper within the iWOAR network is *A study on measuring heart- and respiration-rate via wrist-worn accelerometer-based seismocardiography* (2015) with 74 citations, where 4 only citations come from within the iWOAR community. The most cited paper *Deep Neural Network based Human Activity Recognition for the Order Picking Process* (2017) with 125 citations was only cited 3 times within the own iWOAR community. This indicated a very small Eigenfactor and a high external impact and reach.

3.6 Geographic Diversity

Country affiliations were obtained from the OpenAlex academic database, which provides institutional metadata including country codes. Of the 470 unique iWOAR authors, 401 (85.3%) could be mapped to a country. The remaining 69 authors (14.7%) lack geographic data either because they have no OpenAlex profile (28 authors, primarily from BIB-only entries without DOI) or because their OpenAlex profile does not list an institutional affiliation (41 authors).

Figure 8 provides two views of iWOAR’s geographic reach based on these 401 authors. The left panel shows the distribution across 32 countries. Germany dominates with 201 authors (50% of those with identifiable affiliations), reflecting the

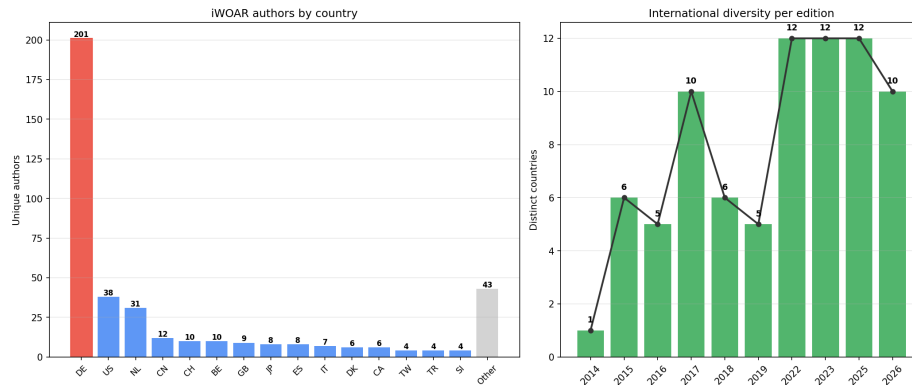


Fig. 8: Left: distribution of iWOAR authors by country (ISO 3166-1 codes). Germany accounts for nearly half of all authors. Right: number of distinct countries represented per edition, showing increasing internationalization since 2022.

workshop’s origins at Fraunhofer IGD Rostock. The United States ranks second with 38 authors, followed by the Netherlands (31), China (12), Switzerland and Belgium (10 each), and the United Kingdom (9). The remaining 26 countries each contribute fewer than 9 authors, spanning Europe, Asia, the Americas, and the Middle East.

The right figure reveals international diversity per edition. The 2014 workshop drew authors from only 1 country (Germany), while iWOAR 2015 already reached 6 countries. After a plateau during the single-location years (2016–2019, 5–10 countries), the post-pandemic editions show a marked increase in diversity: iWOAR 2022, 2023, and 2024 each attracted authors from 12 distinct countries. This trend correlates with the decision to rotate the workshop to new locations and the publisher transition, both of which have increased international visibility.

3.7 Institutional Landscape

Figure 9 shows the top 15 institutions by number of unique iWOAR contributors. These counts are based on per-paper affiliation data from OpenAlex, meaning an author is counted for each institution they were affiliated with at the time of a given publication. The Fraunhofer Institute for Computer Graphics Research (IGD) lead with 26 authors and 30 papers. The University of Siegen follows with 12 unique authors and 9 papers, followed by the University of Rostock and the University of Lübeck. Other reoccurring institutions include the Hasso Plattner Institute, the University of Twente and others. Another international institution, such as the University of Texas at Arlington further illustrate the growing non-German participation.

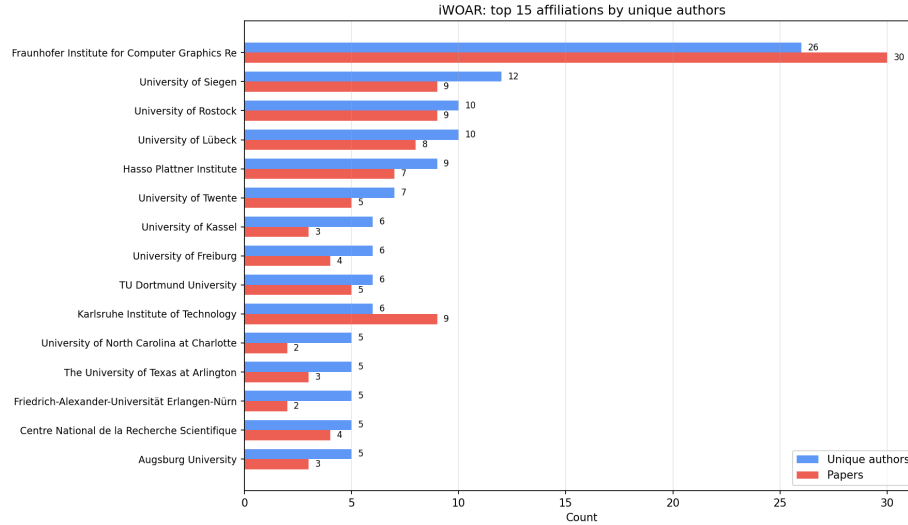


Fig. 9: Top 15 institutions by number of unique iWOAR authors (blue) and associated papers (red), based on per-paper affiliation data from OpenAlex.

4 Keywords & Topics

To systematically assess the thematic evolution of iWOAR over its first decade, we conducted a keyword analysis across the nine english editions from 2015 to 2025. A total of 794 keywords were extracted from 160 papers, normalized to account for spelling variations, abbreviation differences, and capitalization inconsistencies, and subsequently clustered into 65 thematic categories. This analysis provides a quantitative lens for examining the research landscape of sensor-based activity recognition, revealing both enduring themes and emergent directions within the community.

4.1 Most Frequent Keywords and Emerging Topics

Figure 10 presents two complementary views of the keyword landscape. On the left, the 15 most frequently occurring individual keywords after normalization are shown. *Human activity recognition* stands out clearly, appearing in 26 papers (17.1% of all contributions), followed by *machine learning* with 22 occurrences. The top of the ranking is dominated by terms related to activity recognition, learning methods, and wearable sensing, which confirms that these remain the foundational pillars of the workshop.

On the right side, we show the topic clusters that first appeared at iWOAR 2019 or later. These emerging clusters represent some of the most dynamic developments in the community. *Edge AI & On-Device Computing* leads with 15 occurrences, nine of which are concentrated in the 2025 edition alone. This cluster covers TinyML, model compression, quantization, and energy-efficient inference, reflecting a growing interest in processing sensor data directly on embedded devices. *AI Ethics & Regulation* appeared for the first time in 2024 and expanded rapidly in 2025, covering themes such as automation bias, human agency, data sovereignty, and the environmental impact of AI. Other notable newcomers include *WiFi & Radar Sensing*, pointing toward device-free sensing modalities, and *Synthetic Data & Augmentation*, which addresses the persistent challenge of data scarcity through generative approaches.

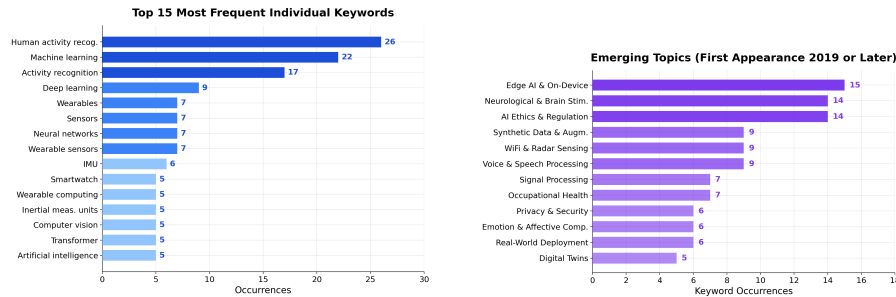


Fig. 10: Left: The 15 most frequently occurring individual keywords across all 152 iWOAR papers after normalization. Right: Emerging topic clusters that first appeared at IWOAR 2019 or later, ranked by total keyword frequency.

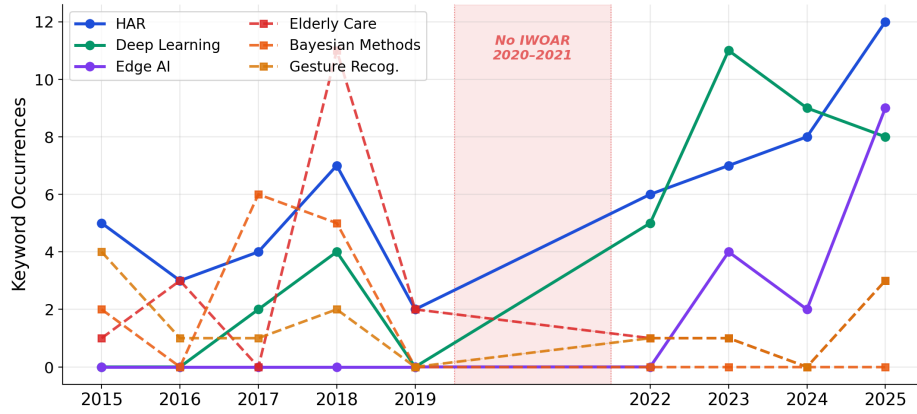


Fig. 11: Contrasting keyword trajectories for selected rising topics (solid lines) and declining topics (dashed lines) across all IWOAR editions. The shaded region marks the COVID-19 hiatus (2020 and 2021) during which no editions were held.

4.2 Topic Evolution

To trace how the major research themes have developed over time, we clustered related keywords and tracked their frequency across editions. Figure 11 shows the evolution of the six largest thematic clusters as a stacked area chart, with the COVID-19 hiatus (2020 and 2021) clearly visible as a gap in the timeline.

Human Activity Recognition has been the dominant cluster throughout all editions, growing from 5 occurrences in 2015 to 12 in 2025. *Machine Learning* and *Deep Learning* are tied with 39 occurrences each, but their trajectories differ in an interesting way: while machine learning has been present since the beginning, deep learning was absent from the first two editions and only gained momentum after 2017. Since 2022, "deep learning" has consistently been among the most prominent clusters, with a peak of 11 occurrences at IWOAR 2023.

The *Wearable Sensors & Devices* cluster (38 occurrences) and *Vital Signs & Physiological Monitoring* (38 occurrences) represent stable foundational themes. The wearable cluster covers everything from smartwatches and smart insoles to data gloves, while vital signs monitoring spans ECG, photoplethysmography, respiration detection, and heart rate variability. A notable observation is the spike in vital signs keywords at IWOAR 2018, which hosted a special focus on physiological measurement.

Human-Computer Interaction was particularly prominent in the early editions, accounting for 7 keyword occurrences in 2015, but has since settled into a more moderate presence. This suggests that HCI considerations have become an integrated part of the research rather than a separate focus area.

Looking at the broader picture, the 65 clusters divide into 16 rising, 13 stable, 16 declining, and 20 emerging topics. The fact that nearly a third of all clusters are entirely new additions from recent editions speaks to the expanding scope of the workshop. Topics like *Elderly Care & Assisted Living* and *Probabilistic &*

Bayesian Methods, which were prominent in the earlier years, have seen reduced presence as research attention has shifted toward deep learning, edge computing, and new sensing modalities.

4.3 Modalities & Models

To complement the thematic keyword analysis, we examined the sensor modalities and machine learning models employed across all 160 papers. Each paper was manually annotated with the sensing modalities used for data acquisition and, where applicable, the classification or regression models applied. We categorized modalities into 16 sensor types and models into 13 distinct classes, covering both traditional machine learning and deep learning approaches.

Sensor Modalities IMU-based sensing (accelerometers, gyroscopes, and combined inertial measurement units) is by far the dominant modality, appearing in 81 papers (50.6% of all publications). Camera and video-based approaches rank second with 35 papers (21.9%), followed by environmental sensors such as temperature, humidity, and barometric pressure (16 papers), PPG (14 papers), and pressure/force sensors (13 papers). Audio-based sensing appears in 11 papers. Notably, IMU usage remains consistently high across all periods, while camera/video-based approaches show steady growth, particularly in 2024–25. Beyond these top modalities, a long tail of specialized sensors includes capacitive sensing (6), EDA (6), WiFi/Radar (5), GPS/UWB/LoRa (5), EEG/EMG (4), IR/thermal (4), RFID (4), CGM (3), and LiDAR (3). The majority of papers (58%) rely on a single sensor modality, while one-third (33%) employ multi-modal sensing setups combining two or more sensor types. The remaining 9% of papers do not specify a concrete sensing modality, as they present surveys, conceptual frameworks, or purely computational contributions.

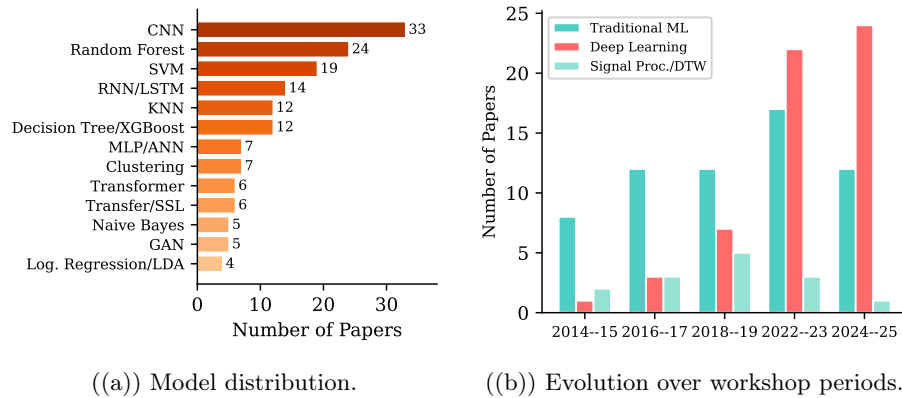


Fig. 12: Machine learning models used in the surveyed papers. (a) Distribution of model types. (b) Evolution of modeling approaches over workshop periods.

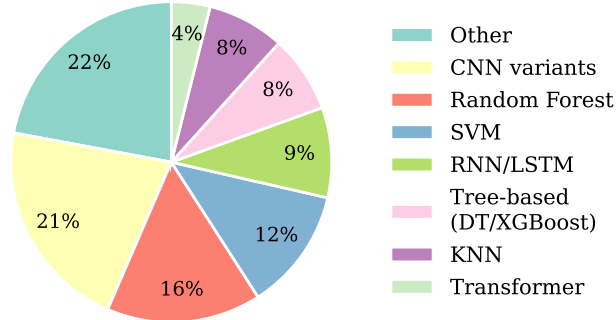


Fig. 13: Grouped model family distribution. CNN variants account for the largest share, while tree-based and kernel methods remain widely used.

Machine Learning Models Of all papers, 88 (55%) employ at least one classifiable machine learning model. The remaining papers either present system designs, surveys, data collection studies, or rely on methods outside the scope of our classification (e.g., pure signal processing pipelines or rule-based heuristics). Figure 12(a) presents the distribution of model types. Convolutional Neural Networks (CNNs) are the most frequently used model class (33 papers), followed by Random Forest (24), SVM (19), and RNN/LSTM architectures (14). KNN and Decision Tree/XGBoost variants each appear in 12 papers. More recent model families such as Transformers (6) and Transfer Learning/Self-Supervised Learning approaches (6) are emerging but remain comparatively rare. Figure 13 provides a grouped view of these model families.

Evolution from Traditional ML to Deep Learning Figure 12(b) reveals a clear temporal shift in modeling paradigms. In the early workshop editions (2014–15), traditional ML methods such as Decision Trees and SVMs dominated almost exclusively, with only a single deep learning contribution. By 2018–19, deep learning had grown substantially but remained roughly on par with traditional approaches. The transition point occurs in the 2022–23 period, where deep learning papers (18) surpass traditional ML (12) for the first time. This trend intensifies in 2024–25, with deep learning (22) now approximately doubling traditional ML usage (11). Surprisingly, 24% of all papers use exclusively deep learning models, while 23% rely solely on traditional ML, whereas 8% compare or combine both paradigms. The substantial share of papers without a classifiable ML model (45%) reflects the workshop’s broad scope, which encompasses hardware prototypes, study designs, and conceptual contributions alongside classification-focused work. Within the traditional ML category, Random Forest seems to be the most popular method (29%), followed by SVM (23%) and KNN (14%). This aligns with the broader HAR literature, where ensemble methods and kernel-based classifiers have long served as strong baselines.

5 Future Directions

5.1 Edge AI and On-Device Inference

Perhaps the most pronounced trend in our data is the rapid rise of Edge AI and on-device computing, which emerged as the leading new keyword cluster with 15 occurrences, nine of them concentrated in the 2025 edition alone. The motivations behind this shift are manifold: latency-critical applications such as fall detection or seizure monitoring demand immediate inference without cloud round-trips; privacy-sensitive health data should ideally never leave the device; and energy constraints in battery-powered wearables make continuous cloud communication impractical. Techniques such as model quantization, pruning, knowledge distillation, and TinyML frameworks are enabling the deployment of deep learning models on microcontrollers with as little as 256 kB of RAM. We expect this direction to intensify as hardware vendors release increasingly capable low-power AI accelerators and as the community develops standardized benchmarks for on-device HAR that jointly evaluate accuracy, latency, and energy consumption. Notably, the deployment of Large Language Models (LLMs) on Edge AI devices for applications such as HAR remains an unexplored frontier at iWOAR. However, given current computational shifts, we anticipate that edge-based LLM research will inevitably permeate the iWOAR community in the near future.

5.2 Digital Twins and Simulation-Driven Development

A recurring challenge in HAR research is the cost of collecting and annotating real-world sensor data at scale. Digital twins, virtual replicas of physical environments, human bodies, or sensor systems, offer a compelling path forward. By simulating realistic sensor outputs for diverse activities, body types, and environmental conditions, digital twins can generate large-scale training data without the overhead of physical data collection. This is particularly valuable for rare or safety-critical events such as falls or industrial accidents, where real data is inherently scarce. Early work in this space, including synthetic data generation from smart floor digital twins presented at iWOAR 2025, demonstrates the feasibility of this approach. We anticipate that the convergence of physics-based simulation engines, generative models, and domain randomization techniques will make simulation-driven development a standard component of the HAR research pipeline, enabling more robust transfer from simulated to real-world deployments.

5.3 Synthetic Data and Generative Augmentation

Closely related to digital twins but distinct in methodology, generative approaches to data augmentation have emerged as a dedicated research thread. Our keyword analysis identified *Synthetic Data & Augmentation* as a new cluster, encompassing GANs, diffusion models, and video-to-IMU synthesis pipelines.

The promise is twofold: first, to address class imbalance and data scarcity, particularly for underrepresented activities or clinical populations; and second, to enable cross-modal transfer, for example generating plausible IMU signals from video recordings of activities. As generative models continue to improve in fidelity and controllability, we expect them to become an integral part of data preprocessing pipelines, reducing the dependency on expensive in-situ data collection campaigns.

5.4 Device-Free and Ambient Sensing

While IMU-based wearables remain the dominant sensing paradigm (appearing in over 50% of all iWOAR papers), our analysis reveals a growing interest in device-free alternatives. WiFi and radar-based sensing appeared as an emerging keyword cluster, and contributions using channel state information (CSI) or millimeter-wave radar for through-wall activity recognition demonstrate the potential of infrastructure-based approaches. These modalities are particularly attractive for applications where wearable compliance is low, such as elderly care or smart home monitoring. Combined with advances in ambient environmental sensing (temperature, air quality, occupancy), device-free approaches could enable truly unobtrusive monitoring systems. The challenge lies in achieving the fine-grained recognition accuracy that body-worn sensors provide, a gap that may narrow as deep learning models become better at extracting activity signatures from noisy ambient signals.

5.5 Responsible AI and Ethical Sensing

Our keyword analysis revealed *AI Ethics & Regulation* as one of the fastest-growing clusters, appearing for the first time in 2024 and expanding rapidly in 2025. This reflects a broader shift in the research community toward responsible technology development. For sensor-based activity recognition, the ethical dimensions are particularly acute: continuous monitoring of human behavior raises fundamental questions about surveillance, consent, data ownership, and the right to not be observed. We expect future iWOAR editions to increasingly engage with privacy-preserving techniques such as federated learning and on-device processing (which also aligns with the Edge AI trend), as well as with questions of fairness, bias in activity recognition systems across diverse populations, and the environmental sustainability of always-on sensing and model training. As HAR systems move from research prototypes into clinical and occupational deployment, establishing transparent and ethically grounded design practices will be essential for maintaining public trust and societal acceptance.

6 Conclusion & Outlook

This paper presented a comprehensive retrospective analysis of the International Workshop on Sensor-Based Activity Recognition and Artificial Intelligence

(iWOAR) across its first decade, spanning ten editions from 2014 to 2025. By systematically examining 160 published papers through keyword analysis, sensor modality categorization, and machine learning model classification, we have provided a quantitative account of how the field of sensor-based activity recognition has evolved within this community.

Our analysis reveals several key findings. First, the workshop has maintained a consistent core identity around human activity recognition and wearable sensing, with IMU-based approaches appearing in over half of all contributions. Second, we observe a clear paradigm shift in modeling approaches: while traditional machine learning methods such as Random Forest and SVM dominated the early editions, deep learning, led by CNNs and RNN/LSTM architectures, has overtaken traditional methods since 2022 and now accounts for roughly twice as many contributions. Third, the keyword analysis uncovers a diversifying research landscape, with 20 entirely new topic clusters emerging in recent editions. Edge AI, ethical considerations, and device-free sensing represent the most dynamic growth areas, while foundational themes such as wearable sensing and physiological monitoring remain stable anchors of the community.

Beyond the technical evolution, iWOAR’s organizational trajectory offers instructive lessons for workshop sustainability. The transition from a locally rooted event at Fraunhofer IGD in Rostock to a rotating, internationally hosted conference has demonstrably increased submission numbers and selectivity. At times, iWOAR showed a competitive acceptance rate of 40%. Similarly, the publisher transition from ACM to Springer in 2024, reflects a principled commitment to the event’s founding ethos as an inclusive forum by researchers, for researchers.

Looking ahead, iWOAR is well positioned to serve as a venue where the trajectories identified in this analysis converge. The push toward on-device inference, synthetic data generation through digital twins, and privacy-preserving sensing architectures are not independent trends but deeply interconnected: edge deployment demands lightweight models, which in turn benefit from simulation-generated training data, and processing data locally is itself a privacy-preserving design choice. We expect future papers to also tap on research with LLMs, particularly because these models become increasingly light-weight and deployable in Edge AI. Future iWOAR editions are expected to feature contributions at these intersections, alongside a growing engagement with responsible AI practices as HAR systems transition from controlled laboratory studies to real-world deployment in healthcare, industry, and daily life.

The data presented in this paper is intended not only as a historical record but as a resource for identifying underexplored research gaps and for situating new contributions within the broader arc of the field.

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