Emerging trends in biomedical trait-based human identification: A bibliometric analysis

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Review

Emerging trends in biomedical trait-based human identification: A bibliometric analysis

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ABSTRACT

Personal human identification is a crucial aspect of modern society with applications spanning from law enforcement to healthcare and digital security. This bibliometric paper presents a comprehensive analysis of recent advances in personal human identification methodologies focusing on biomedical traits. The paper examines a diverse range of research articles, reviews, and patents published over the last decade to provide insights into the evolving landscape of biometric identification techniques. The study categorizes the identified literature into distinct biomedical trait categories, including but not limited to, fingerprint and palmprint recognition, iris and retinal scanning, facial recognition, voice and speech analysis, gait recognition, and DNA-based identification. Through systematic analysis, the paper highlights key trends, emerging technologies, and interdisciplinary collaborations in each category, revealing the interdisciplinary nature of research in this field. Furthermore, the bibliometric analysis examines the geographical distribution of research efforts, identifying prominent countries and institutions contributing to advancements in personal human identification. Collaboration networks among researchers and institutions are visualized to depict the knowledge flow and collaborative dynamics within the field. Overall, this study serves as a valuable reference for researchers, practitioners, and policymakers, shedding light on the current status and potential future directions of personal human identification leveraging biomedical traits.

1. Introduction

Personal human identification, the precise and unique determination of an individual's identity, is an essential requirement across various sectors, including law enforcement, healthcare, financial services, and digital security. Traditional identification methods like passwords and PINs have demonstrated vulnerabilities and susceptibility to breaches, highlighting the pressing need for more secure and dependable identification techniques. Responding to this necessity, the integration of biomedical traits for identification purposes has garnered substantial attention, offering a promising avenue to enhance identification accuracy and security. Biomedical traits, distinguished by their inherent uniqueness and stability, form a robust foundation for personal identification. This category encompasses an array of physiological and behavioral characteristics, ranging from the distinct patterns of fingerprints and palmprints to the intricate features of iris and retinal scans [1–3]. The expanding repertoire of identification

modalities includes facial features, voice patterns, gait dynamics, and even the genetic signatures encoded within DNA profiles [4–6].

Recent years have witnessed remarkable advancements in research and development within the realm of personal human identification methods centered around biomedical traits. Fig. 1 presents a thematic map highlighting the various dimensions of biomedical trait-based human identification research. Driven by technological progress and interdisciplinary collaborations, this field has witnessed the exploration of innovative techniques and tools that leverage the inherent characteristics of these traits. These advancements carry the potential to revolutionize identification processes, mitigating false positives and negatives, bolstering security measures, and enhancing user convenience. The interdisciplinary nature of this field becomes evident through the convergence of diverse domains, including biometrics [6, 7], computer vision [4,8], machine learning [9,10], and genetics [11].
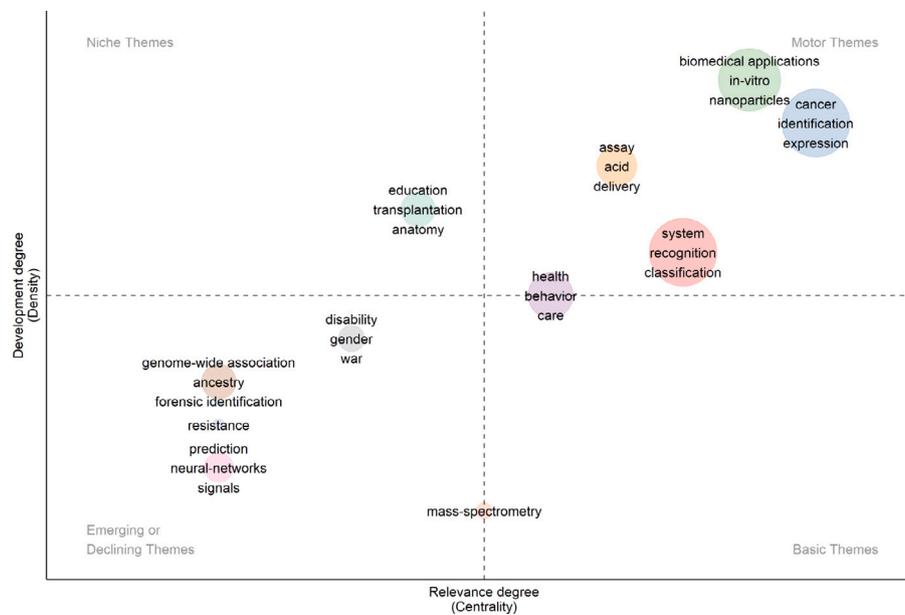

Fig. 1. Thematic landscape of biomedical trait-based human identification research.

Researchers from varied backgrounds collaborate to design, implement, and validate identification systems that seamlessly integrate technological innovation with the distinctiveness of biological traits.

As this field rapidly evolves, it is imperative to gain a comprehensive understanding of recent advances, emerging trends, and potential challenges in personal human identification based on biomedical traits. This bibliometric study endeavors to provide an in-depth analysis of the literature published over the last decade, shedding light on the trajectory of research in this domain. By categorizing and dissecting the various identification modalities, examining collaborative networks, and addressing ethical considerations, this paper aims to offer valuable insights for researchers, practitioners, and policymakers seeking to navigate the landscape of personal human identification in the era of advanced biomedical trait analysis.

1.1. Rationale and motivation of the current study

The motivation behind this bibliometric study stems from the increasing importance of personal human identification and its wide-ranging impact across various sectors. In our interconnected digital world, where online interactions are prevalent, the need for reliable identification methods is paramount. Conventional identification measures often fall short in ensuring security, leading to issues such as data breaches, identity theft, and unauthorized access. Hence, there is a growing interest in exploring identification methods based on biomedical traits due to their inherent uniqueness and resistance to duplication. Some key technologies shaping advancements in biomedical trait-based human identification, offering insights into future research directions and opportunities are outlined below:

- **Facial Recognition**: Facial recognition technology has gained significant traction in recent years, finding applications in law enforcement, security systems, and mobile devices. Progress in deep learning algorithms has notably enhanced the accuracy and reliability of facial recognition systems, facilitating the efficient identification of individuals based on facial features [12,13].
- **DNA Profiling and Forensic Genomics**: DNA profiling remains one of the most dependable techniques for human identification [14,15]. Recent advancements in forensic genomics, including next-generation sequencing (NGS) and high-throughput DNA analysis platforms, have revolutionized the field by enabling rapid and comprehensive DNA analysis, thereby serving as invaluable tools in forensic investigations [16].

- **Biometric Modalities Beyond Fingerprinting**: While fingerprinting has been a cornerstone of biometric identification [17], emerging modalities such as iris recognition [18], voice recognition [19], and gait analysis [20] are gaining prominence. Iris recognition systems utilize unique iris patterns for high-accuracy authentication, while voice recognition analyzes vocal characteristics. Gait analysis, examining individual walking patterns, holds promise for identification in surveillance and security applications [21].
- **Implantable Biochips and Biometric Implants**: Implantable biochips and biometric implants represent cutting-edge approaches to human identification [22]. Embedded under the skin, these devices utilize biometric data or physiological markers for authentication, offering potential for seamless and unobtrusive identification in various contexts [23].
- **Brainwave-based Authentication**: Brainwave-based authentication methods leverage unique brain activity patterns for identity verification. Techniques such as Electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI) capture brainwave signals [24], enabling the development of robust authentication systems with enhanced security compared to traditional biometric methods [25,26].
- **Emerging Trends in Biometric Data Fusion**: Integrating multiple biometric modalities through data fusion techniques shows promise in enhancing the accuracy and reliability of human identification systems [27]. By combining information from various sources, researchers [28] can develop more robust authentication systems resilient to spoof attacks and environmental variations.

By systematically aggregating and analyzing a diverse range of research articles, reviews, and surveys, this paper serves as a curated repository of knowledge. It assists researchers and practitioners in staying updated with the latest developments in the field. The insights gleaned from this study have broad implications, ranging from aiding law enforcement in criminal identification to improving patient management and personalized treatment protocols in healthcare. Additionally, industries dealing with user authentication, such as fintech and digital platforms, stand to benefit from the heightened security afforded by these advancements. Moreover, by categorizing and scrutinizing each identification modality, the current work facilitates the identification of trends, gaps, and areas ripe for further exploration, thereby guiding researchers towards promising avenues for future investigation.

2. Bibliometric analysis and data collection

This section offers a comprehensive outline of the bibliometric analysis, along with the specifics of the data acquisition, data collection, and data preparation utilized for the present study.

Bibliometric analysis serves as a valuable complement to traditional methods of assessing literature, providing an objective evaluation of trends and prospects within a specific field. Esteemed scholars such as Sekhar et al. [29], Sharma et al. [30], Kansal et al. [31], and Ye et al. [32] have highlighted the importance of this analytical approach. It proves particularly advantageous for tracking the evolution of a field over extended timeframes, spanning from years to decades, as emphasized by Kaushal et al. [33]. In the realm of reviewing scientific research advancements, a range of methodologies exists, each tailored to the intricacies of a given topic [34]. These methodologies predominantly fall into evaluative and relational reviews [35].

Evaluative reviews offer quantitative assessments of research impact, encompassing factors such as publication counts, annual output, citation metrics, and more, as elucidated by Jamal et al. [36]. Additionally, qualitative evaluative reviews may incorporate expert opinions to gauge research impact [37]. In contrast, relational review methodologies center on understanding the interconnectedness between these evaluative measures. This involves exploring collaborative output volume, partnership linkages, and the strengths of these connections. Techniques like citations-based associations, co-occurrence analyses, and co-citation metrics provide valuable insights into these relational dynamics [38].

The interplay among co-authors signifies the transfer of knowledge across diverse research clusters [39], and understanding research linkages requires an examination of citation interdependencies [40]. Moreover, the strength of collaborations and co-citations across geographical boundaries hinges on the robustness of these linkages [41].

The present study employs a combination of evaluative and relational techniques to achieve a comprehensive bibliometric analysis of biomedical trait-based human identification research. Bibliometric analyses, as discussed by van Raan [42], provide insights into the development of research fields over the past decade. These analyses provide essential information about the research outputs of individual authors and their affiliated institutions [43], as well as citation and collaboration networks encompassing articles, authors, institutions, and geographical locations [44]. They also shed light on emerging trends, influential keywords [37], prominent publishing journals, and inter-journal linkages [45,46], among other facets.

The utilization of data visualization tools is paramount in effectively presenting study findings and swiftly drawing actionable insights [47]. For this study, VoSviewer and CiteSpace were utilized to quantitatively analyze and visually represent the biomedical trait-based human identification research published in the Web of Science (WoS) from 2003 to 2023. VoSviewer, utilizing the bibliometric analysis of collaboration and citation data, develops author and journal network maps. Furthermore, it creates keyword maps that depict the connections among different co-occurring phrases within the subject of study [48]. In parallel, CiteSpace, a Java program, is designed for visualizing citation networks [49], co-authorship relationships, time series analysis of significant topics, as well as keywords and reference bursts [50].

2.1. Data acquisition, collection, and pre-processing

The present bibliometric analysis is conducted using the Web of Science (WoS) repository as the chosen research database. The WoS is well-known for curating an extensive array of impactful research papers from globally recognized publications, encompassing indexed journal publications dating back to 1990. The search string used for the WoS database is (((Personal OR Human) NEAR/5 (Identificat* OR recogni*)) AND Biomedical). The search spanned two decades, starting from 2003. Executed on August 14, 2023, this query resulted in a dataset of 326 research papers in plain text format, aligning precisely with keywords related to biomedical trait-based human identification. This comprehensive search strategy ensured meticulous precision in capturing documents integral to the subject matter under investigation.

3. Descriptive analysis

In this section, the distribution of retrieved publications is elaborated based on factors such as annual publications, publication types, source titles, biomedical and human trait themes, and patterns. Furthermore, the prime contributing countries, organizations, authors, and nationalities in the field of biomedical trait-based human identification research are showcased, along with their corresponding publication counts.

3.1. Yearly publication trends

Fig. 2 portrays the development of publications in the biomedical trait-based human identification field within the Web of Science database over the years. The *x*-axis spans from 2003 to 2023, representing publication years and the *y*-axis denotes the count of WoS publications. Remarkably, a substantial surge in publications related to biomedical trait-based human identification has been observed from 2015 onward. This trend has intensified since 2020, reflecting an increasing interest and demand for research in this domain. It is noteworthy that the number of biomedical trait-based human identification papers published in WoS during 2022 exceeds the number of articles published in the early stages of the field's establishment by over four times.

In recent years, the field of biomedical trait-based human identification has witnessed a remarkable surge in research activity, propelled by significant technological advancements. Notably, the development of advanced biometric sensors capable of capturing high-resolution physiological data has revolutionized the accuracy and precision of biometric identification. Concurrently, the integration of sophisticated machine learning algorithms has enabled the extraction and classification of intricate biometric features with unprecedented efficiency. Furthermore, the adoption of blockchain technology has introduced a paradigm shift in data security and authentication, ensuring the integrity and confidentiality of biometric information. Additionally, the emergence of cloud computing and edge computing solutions has facilitated real-time processing and analysis of biometric data, empowering seamless and instantaneous identification capabilities. This surge in research activity can be attributed to the growing demand for robust and reliable identification methods, particularly in critical sectors such as law enforcement and digital security. The imperative to combat identity theft, enhance access control, and safeguard sensitive information has spurred researchers to explore innovative approaches and technologies in the realm of human identification. By leveraging these technological advancements and addressing the evolving challenges in biometric identification, researchers are poised to unlock new frontiers in personal identification methods, ultimately advancing security, efficiency, and convenience in various domains.

This trend is prominently depicted in Fig. 3, showing a significant exponential increase in the citations received by WoS publications related to biomedical trait-based human identification.

3.2. Publication type

The search in the WoS database yielded a collective of 326 publications related to biomedical trait-based human identification. These encompassed a variety of formats, including research articles, conference papers, review papers, early access documents, and more. Fig. 4 illustrates the distribution of these publication categories and their respective counts. Among them, research articles constitute a substantial portion, accounting for 277 publications or 84.97% of the
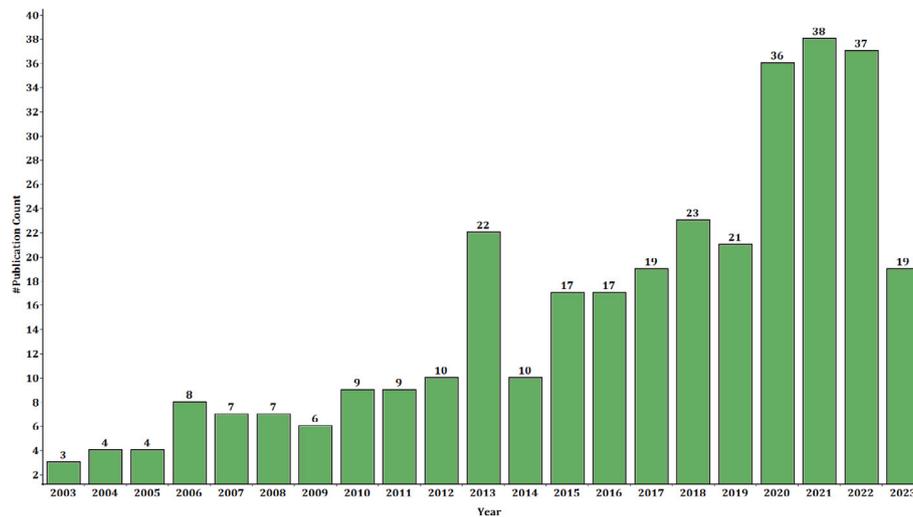
Fig. 2. Yearwise publication count in biomedical trait-based human identification research [2003~2023].
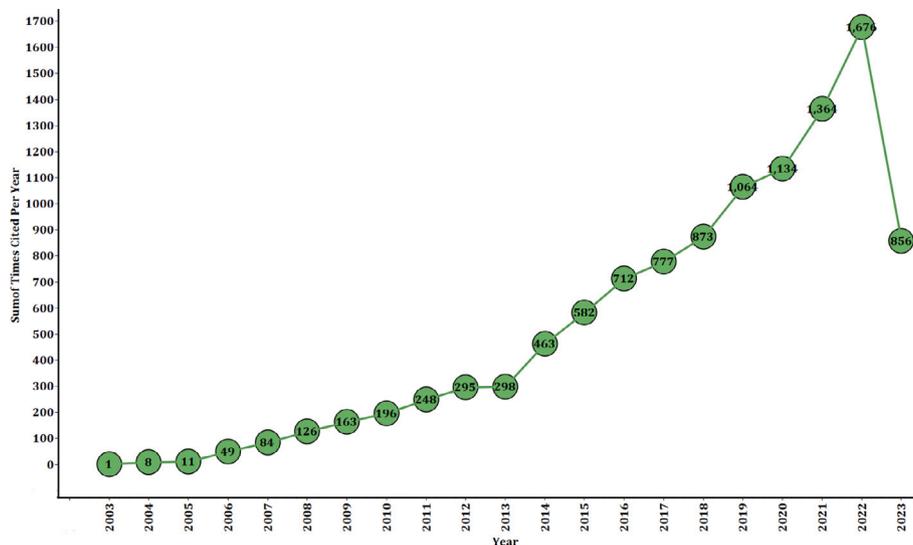
Fig. 3. Yearwise citation count in biomedical trait-based human identification-related publications per year [2003~2023].

total. The second-largest category is review articles, comprising 42 publications and contributing 12.88% to the entire corpus. Proceeding papers constitute 10 publications or 3.07% of the total. Editorial materials account for 7, early access papers for 3, and book chapters for 1 publication, representing 2.15%, 0.92%, and 0.31% of the total documents, respectively.

3.3. Publication source

This subsection highlights the leading sources that publish research related to biomedical trait-based human identification and are indexed in WoS. Fig. 5 illustrates these sources along with the number of articles published by each. According to the distribution analysis by source, the journal 'IEEE Access' has published the highest number of articles (13), constituting 3.99% of all published content on the topic of biomedical trait-based human identification. The second-highest publishing source is 'IEEE Sensors Journal' with 8 publications (2.45%). 'BMC Bioinformatics' and 'IEEE Journal of Biomedical and Health Informatics' tie for the third-highest count with 6 articles each (1.84%). The rest top listed journal publishers include 'Biocybernetics and Biomedical Engineering', 'IEEE Transactions on Biomedical Circuits and Systems', 'International Journal of Molecular Sciences', 'Journal of Molecular

Recognition', 'PLOS One', and 'Sensors,' each contributing 5 articles (1.53%). The subsequent subsection presents an overview of the top organizations worldwide whose members have authored a significant number of articles indexed in WoS.

3.4. Key researchers and organizations

In this section, an examination is conducted on the leading ten institutions that have published articles concerning biomedical trait-based human identification in the Web of Science from 2003 to 2023. As depicted in Fig. 6, both the 'Chinese Academy of Sciences, China', and the 'University of London, United Kingdom', share the distinction of publishing a maximum of 12 articles in this field. Following closely, the 'Tabriz University of Medical Sciences, Iran', secured the second-highest position by contributing 11 WoS articles during the period spanning 2003 to 2023. 'Harvard University, USA', and the 'N8 Research Partnership, United Kingdom', attained the third rank with 10 publications each, while the 'National Institutes of Health, USA', and the 'University of California, USA', each made significant contributions with 8 articles. Furthermore, researchers at the 'Université de Picardie Jules Verne, France', presented 7 articles on biomedical trait-based human identification, followed by the 'Centre National de la Recherche Scientifique,

Fig. 4. Key categories of the 326 biomedical trait-based human identification-related publication types.
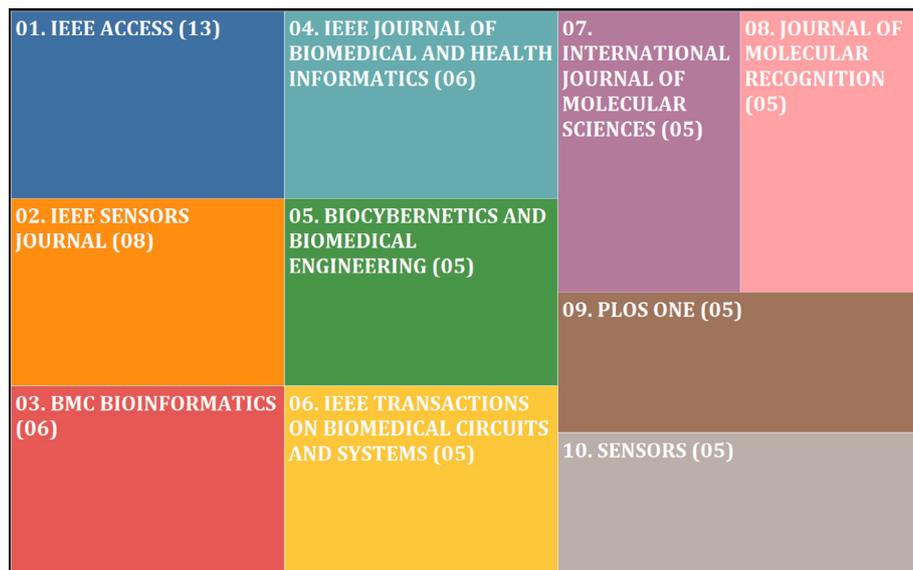
Fig. 5. Key publication titles in the 326 biomedical trait-based human identification-related publications.

France', and the 'Egyptian Knowledge Bank, Egypt' each showcasing 6 articles. This analysis underscores the notable roles played by authors from China, the United Kingdom, and Iran in advancing biomedical trait-based human identification research in the last two decades.

Table 1 provides an overview of the top 10 researchers who have contributed the most to WoS publications in the field of biomedical trait-based human identification. Among these prominent authors, four originate from Spain, two are affiliated with the USA, while the remaining authors hail from Iran, Belgium, Australia, and England, each represented by a single researcher.

3.5. Geographical distribution of research contributions

This subsection spotlights the top 10 countries driving advancements in the field of biomedical trait-based human identification within the WoS repository. These nations, including the United States, People's Republic of China, England, Canada, Germany, Italy, Australia, India, South Korea, and France, have made substantial contributions. The publication output trends of these nations from 2003 onwards are visually depicted in Fig. 7. Notably, the United States leads the pack with a significant contribution of 84 WoS research papers. The People's Republic of China consistently secures the second-highest position, maintaining a strong presence with 54 WoS papers followed by England contributing 36 WoS papers, while Canada closely follows with 22 WoS publications. Among other prominent nations in this list, Germany and Italy each provide 18 WoS papers, with Australia and India presenting 17 WoS papers each. South Korea and France also demonstrate their dedication with 16 and 15 WoS papers, respectively. Impressively, all top ten contributors showcase an upward trajectory in their research outputs over the considered timeframe.

3.6. Key research areas

This section presents the key thematic domains explored by researchers in the field of biomedical trait-based human identification. As depicted in Fig. 8, a significant focus is evident in the domain of 'Engineering' with 86 articles, as reflected in the scope of WoS publications. Following closely is the domain of 'Computer Science', which
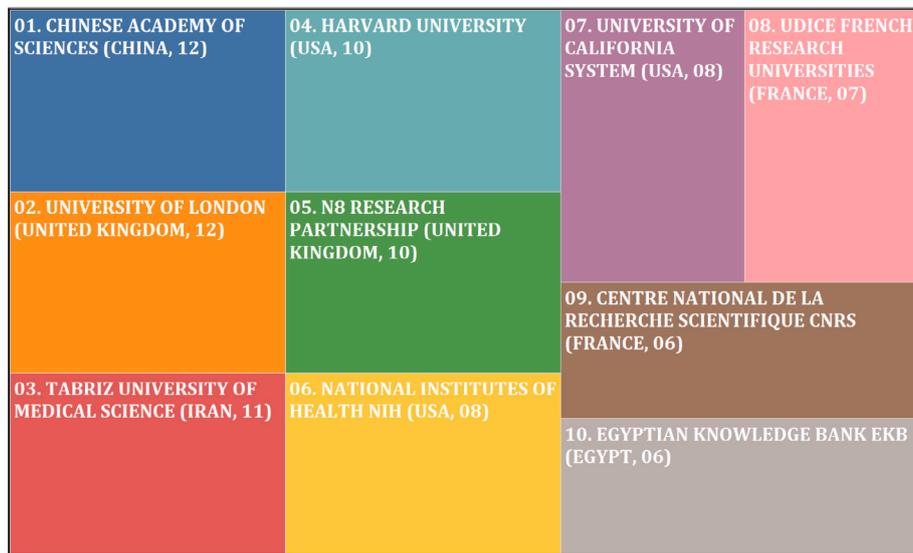
Fig. 6. Key organizations in the 326 biomedical trait-based human identification-related publications.

Table 1
Key authors in biomedical trait-based human identification research.

| Sr.No.	Author	Institution	Record
1.	Hasanzadeh, Mohammad	Nutrition Research Center, Tabriz University of Medical Sciences, Tabriz, Iran	11
2.	Albero, Ginesa	Catalan Institute of Oncology (ICO), Lhospitalet De Llobregat, Barcelona, Spain	4
3.	Arbyn, Marc	Science Institute for Public Health, Cancer Epidemiol Unit, Brussels, Belgium	4
4.	Xavier Bosch, F.	Catalan Institute of Oncology (ICO), Lhospitalet De Llobregat, Barcelona, Spain	4
5.	Broker, Thomas R.	University of Alabama, Birmingham, USA	4
6.	Brotons, Maria	Catalan Institute of Oncology (ICO), Lhospitalet De Llobregat, Barcelona, Spain	4
7.	Canfell, Karen	Prince Wales Clinton Sc, Lowy Cancer Research Centre, Sydney, Australia	4
8.	Castellsague, Xavier	Consortium for Biomedical Research in Epidemiology & Public Health, Madrid, Spain	4
9.	Castle, Philip E.	Global Cancer Initiative, Maryland, USA	4
10.	Cuzick, Jack	Queen Mary University of London, London, England	4
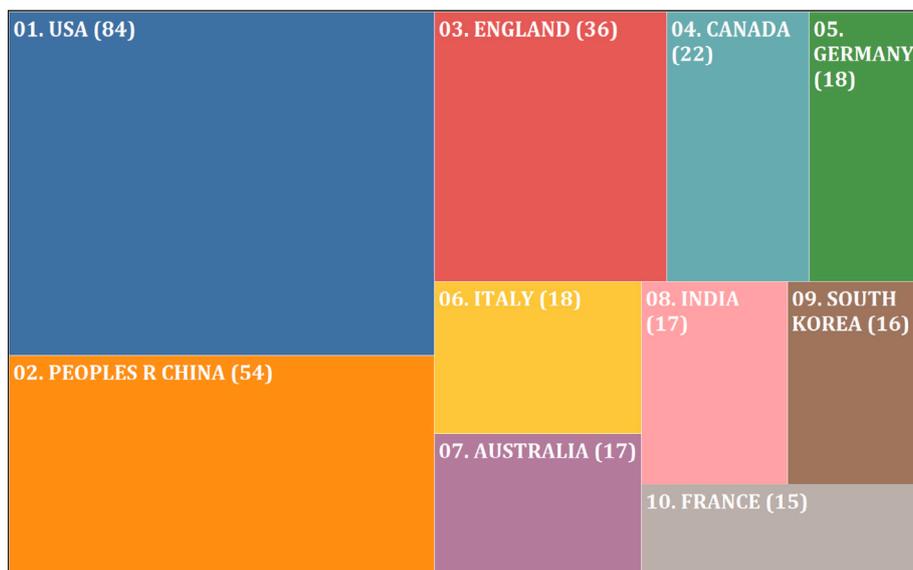
Fig. 7. Key countries in the 326 biomedical trait-based human identification-related publications.
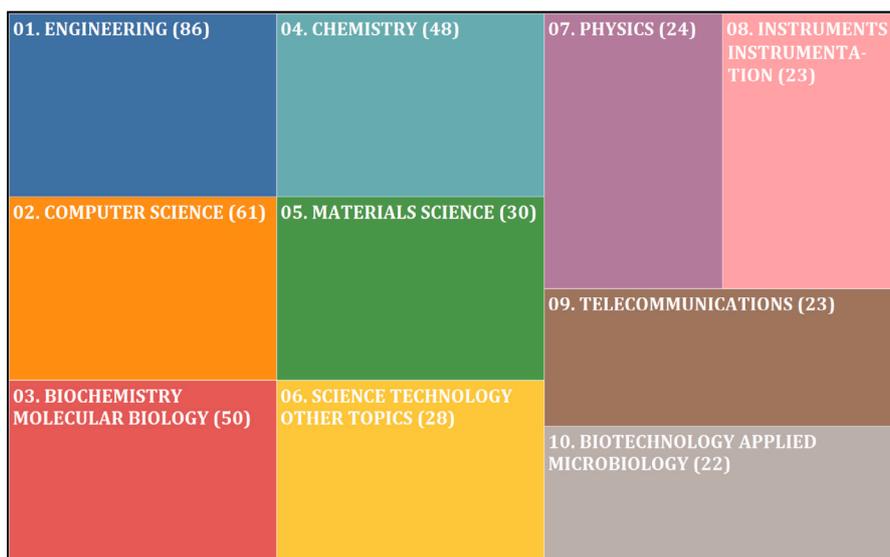
Fig. 8. Key research areas in the 326 biomedical trait-based human identification-related publications.

accounts for 61 papers. The field of 'Biochemistry Molecular Biology' emerges as the third most prominent area, encompassing 50 papers related to biomedical trait-based human identification. Additionally, the domain of 'Chemistry' contributes 48 WoS articles. Notably, the domains of 'Materials Science' and 'Science Technology other topics' exhibit interesting trends, housing 30 and 28 WoS papers, respectively, aspects that might not be immediately apparent in the contemporary research landscape. Moreover, the domain of 'Physics' includes 24 WoS articles, highlighting the integration of biomedical trait-based human identification with applied sciences. An additional 23 articles are dedicated to 'Instruments Instrumentation' and 'Telecommunications' emphasizing the subject's relevance in areas involving pattern matching, image capture, recognition, and analysis. The domain of 'Biotechnology Applied Microbiology' also engages with this theme, as evidenced by 22 WoS articles dedicated to biomedical trait-based human identification applications.

3.7. WoS indexing and categorization

This subsection presents the distribution of research articles related to biomedical trait-based human identification across prominent indices within the Web of Science. As illustrated in Fig. 9, the distribution includes the number of articles that have been both published and indexed in the WoS corpus indices. Most WoS publications (319) are in the 'Science Citation Index Expanded'. The 'Social Sciences Citation Index' is the second highest with 30 articles, indicating journals that publish high-quality research. Notably, there are 10 articles in the 'Conference Proceedings Citation Index Science (CPCI-S)' each. This is significant because conference publications are where researchers share early research findings and get feedback from the scientific community. This shows how diverse biomedical trait-based human identification research is, covering various fields of science and technology. One article even finds its place in the 'Book Citation Index Science (BKCI-S)' among these indices.

Fig. 10 visualizes the distribution of publications related to human identification, categorized by Web of Science across various domains. The analysis reveals a predominant focus on 'Engineering Electrical Electronic' which encompasses the highest number of publications (55). This points to a substantial body of work addressing aspects of electrical and electronics engineering within the context of human identification. 'Engineering Biomedical' emerges as the second-highest category (30), with a significant representation of research articles concerning human identification within the biomedical engineering

field. This is followed by 'Computer Science Information Systems', accounting for 29 publications, highlighting the intersection of human identification research with computer science. 'Biochemistry Molecular Biology' emerges as the fourth substantial category, comprising 27 articles, while 'Biochemical Research Methods' closely follows with 26 publications. Additionally, 'Instruments Instrumentation', 'Materials Science', and 'Telecommunications' stand out as notable contributors, each housing 23 articles. Within the top ten categories, 'Biotechnology Applied Microbiology' and 'Computer Science Interdisciplinary Applications' exhibit substantial engagement with the subject matter, contributing 22 and 21 articles respectively to the WoS corpus.

Overall, considering the research trends, the consistent appearance of over 326 publications annually indicates a sustained interest and activity in the field. Engineering emerges as the dominant research area, with a notable emphasis on biomedical monitoring. Researchers may find it fruitful to explore interdisciplinary collaborations and innovative approaches within this area. Moreover, publication outlets and geographic distribution, including journals such as IEEE Access and institutions like the Chinese Academy of Sciences, demonstrate significant contributions to the literature. This highlights the importance of targeting reputable journals and fostering international collaborations to enhance research impact and visibility.

4. Co-authorship analysis

Effective collaboration is pivotal in producing impactful research results. Collaborations that span across departments, institutions, and even international borders foster the exchange of innovative ideas and strategies to tackle shared challenges. In this regard, inter-departmental, inter-institutional, and international partnerships are recognized as vital components that contribute to the advancement of knowledge and solutions. The following sections provide a thorough exploration of the various collaborative dimensions within the realm of biomedical trait-based human identification, utilizing insights derived from a meticulous bibliometric analysis. To unearth and examine these insights, we harnessed the capabilities of the VoSviewer software.

4.1. Author-based co-authorship analysis

This subsection unveils an analysis of co-authorship dynamics among researchers engaged in the publication of biomedical trait-based human identification research within the last ten years. The exploration was initiated through a VoSviewer search, which yielded a cohort
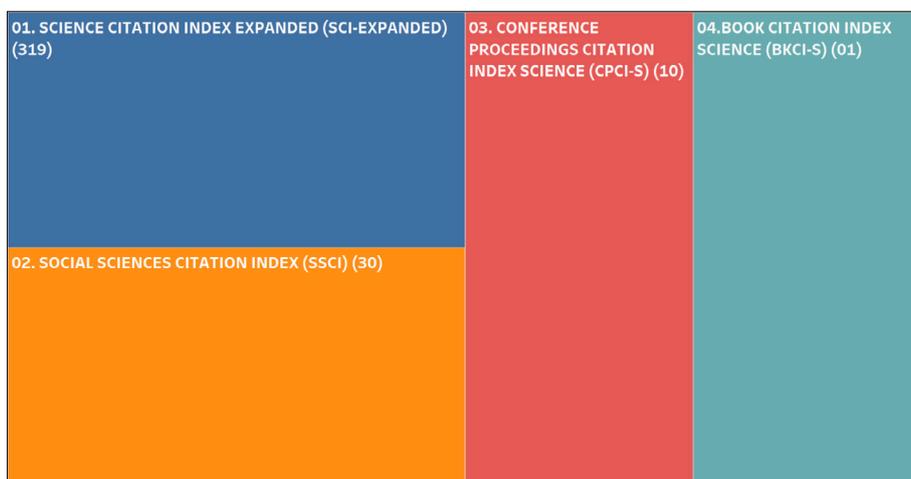
Fig. 9. Key web of sciences indexes in the 326 biomedical trait-based human identification-related publications.
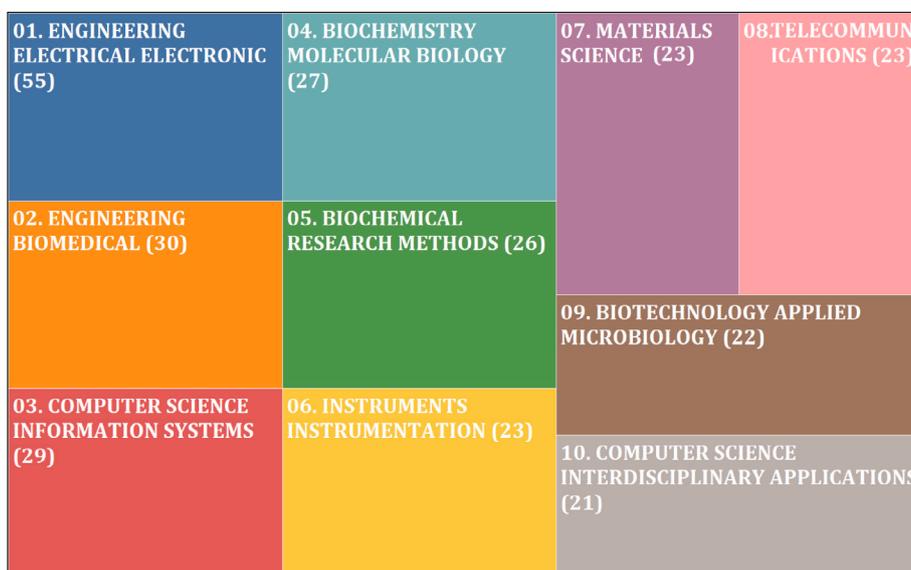
Fig. 10. Key web of sciences categories in the 326 biomedical trait-based human identification-related publications.

of 1466 such authors. Employing the fractional counting method for co-authorship assessment, a threshold was applied, necessitating each author to have a minimum of 2 published documents and 2 citations [51]. Among the initial group, only 74 authors met the specified criteria, with 42 authors establishing the most extensive network of co-authorship connections.

Table 2 offers a clear overview of the top researchers ranked by TLS, revealing that among them, seven are based in China. The USA, England, and Taiwan each contribute one researcher to this list. This underscores that the leading ten researchers in biomedical trait-based human identification hail from just four nations. Noteworthy is the fact that Wang, Xiao (China) stands at the forefront with the highest TLS score of 16. Meanwhile, Wang, Yue (USA), Yang, Yan (China), and Zhang Ying (China) all share an identical TLS score of 10, along with 10, 9, and 9 co-author links, respectively. Similarly, other notable contributors include Li, Yi (England), Wang, Hao (China), Li, Ching-Chia (Taiwan), Xu, Shuhua (China), and Zhang, Han (China).

Fig. 11 illustrates a visualization of the collaboration network among researchers engaged in biomedical trait-based human identification research, along with their interconnected relationships. The diagram employs distinct colors to delineate various network clusters,

Table 2
Key researchers (P: Publications, L: Links, TLS: Total Link Strength).

Rank	Researcher	Country	P	L	TLS
1	Wang, Xiao	China	3	16	16
2	Wang, Yue	USA	3	10	10
3	Yang, Yan	China	3	9	10
4	Zhang, Ying	China	3	9	10
5	Li, Yi	England	4	9	9
6	Wang, Hao	China	4	9	9
7	Li, Ching-Chia	Taiwan	2	9	9
8	Xu, Shuhua	China	2	8	9
9	Zhang, Han	China	2	8	9
10	Zhang, Chao	China	3	8	8

while the thickness of the links corresponds to their associated link strengths, as visually represented. Within this depiction, notable top Total Link Strength (TLS) authors such as Wang X (blue node), Zhang Y (yellow node), Zhang X (blue node), Yan S (blue node), and Wang Y (blue node) stand out as closely linked entities within the co-author networks.

Fig. 11. Author's co-authorship network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Organization-based co-authorship analysis

This subsection introduces co-authorship interactions among organizations analysis that have contributed to the publication of biomedical trait-based human identification research over the past two decades. The starting point of this exploration was a VoSviewer search, which resulted in a compilation of 614 such organizations. For the purpose of co-authorship evaluation, the fractional counting method was applied, with a stipulated requirement of atleast 3 publications and 3 citations per organization. To streamline the analysis, documents co-authored by over 25 organizations were excluded from consideration. As a result of these criteria, a total of 48 organizations were deemed eligible for inclusion. Among them, 28 organizations collectively formed a substantial interconnected network. From the initial set of 614 organizations, Table 3 highlights the top 13 organizations based on their co-authorship-oriented TLS values.

Within the list of leading institutions, four institutions are from the USA, two from Canada and England, and one each from Spain, France, Australia, and Belgium. Interestingly, all the top-listed organizations have a TLS of 93 and a co-author linkage count of 24. Fig. 12 presents the collaboration network map of institutions engaged in biomedical trait-based human identification research, showcasing their interconnected relationships. The nodes on the network grid represent significant organizations with the highest co-authorship TLS, and their connections are depicted with the same color, indicating equal TLS. These visualizations offer a coherent perspective of the collaborative networks and research dynamics among institutions in the domain of biomedical trait-based human identification.

4.3. Country-based co-authorship analysis

In this subsection, we delve into a co-authorship analysis concerning the nations engaged in the publication of biomedical trait-based human identification research over the preceding two decades. To initiate this exploration, a VoSviewer search generated a comprehensive compilation of 67 nations that have contributed to this field. Employing the fractional counting method, the co-authorship relationships between these nations were scrutinized. Specifically, a prerequisite threshold

Table 3
Key institutions (P: Publications, L: Links, TLS: Total Link Strength).

Rank	Institutions	P	L	TLS
1	Centers for Disease Control and Prevention, USA	4	24	93
2	Global Cancer Initiative, USA	4	24	93
3	Harvard University, USA	7	24	93
4	IDIBELL, Spain	4	24	93
5	Institut National de Sante Publique du Quebec, Canada	4	24	93
6	International Agency for Research on Cancer, France	4	24	93
7	McGill University, Canada	5	24	93
8	National Institute for Medical Research, England	4	24	93
9	National Cancer Institute, USA	4	24	93
10	NSW Cancer Council, Australia	4	24	93
11	The Ohio State University, USA	4	24	93
12	Queen Mary University of London, England	5	24	93
13	Scientific Institute of Public Health, Belgium	4	24	93

was set, demanding a minimum of 3 publications and 3 citations per country for inclusion in the analysis. For the sake of focus and precision, publications co-authored by more than 25 countries were excluded from consideration. As a result of these stringent criteria, a total of 36 countries were deemed eligible for inclusion in the co-authorship analysis.

Among these nations, a notable network of 34 interconnected countries emerged. From this network, Table 4 highlights the top ten countries based on their Total Link Strength (TLS) values, which serve as an indicator of the intensity of co-authorship collaboration among these nations.

Among the top-listed countries, England ranks at the top with the highest TLS (23) alongside 36 publications. The USA follows with the second-highest TLS (68), accompanied by 84 publications, while France holds a TLS count of 50 and 15 publications. Additionally, Canada and Australia share an equal TLS of 43, however, Canada's contribution comprises 22 publications, while Australia's count stands at 17. Further within the list of leading countries are five European nations—Netherlands, Spain, Belgium, Slovenia, and Italy. The remaining selection includes two Asian countries, China and India, along with the African nation of South Africa.

Fig. 12. Organization's co-authorship network in the field of biomedical trait-based human identification.
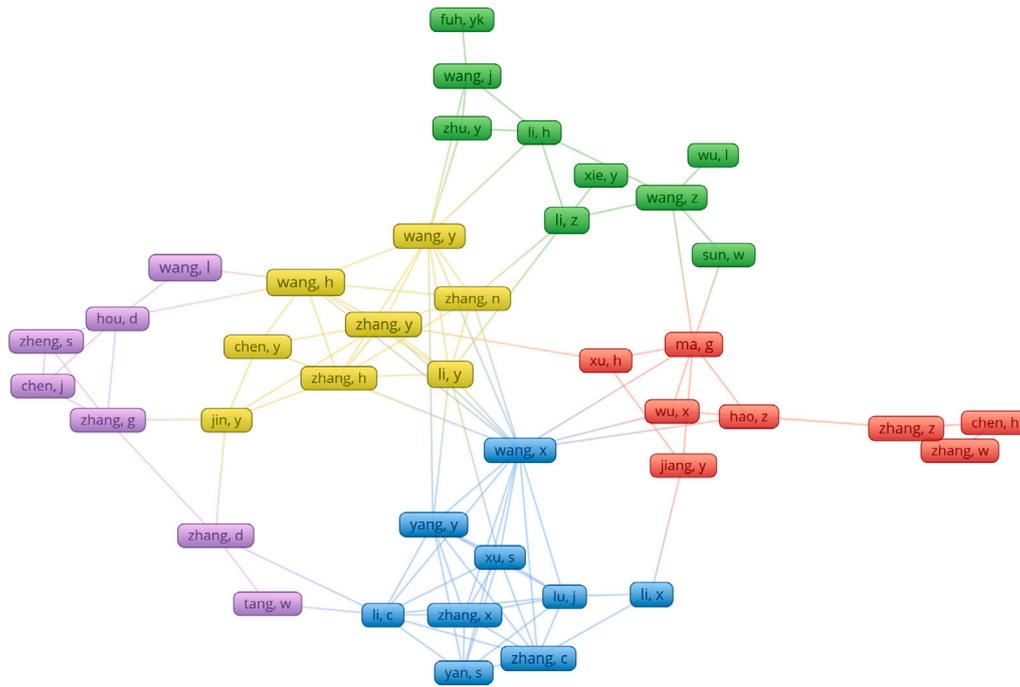

Fig. 13. Countries co-authorship network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 13 illustrates the collaboration network map among countries engaged in biomedical trait-based human identification research, highlighting their interconnected relationships. The figure showcases a network of nations including the USA, China, England, Singapore, and Japan, all interlinked within a co-author network depicted in red. Similarly, a green network emerges, connecting South Korea, India, Egypt, Russia, Saudi Arabia, and Turkey. The blue network predominantly comprises European countries such as Slovenia, Spain, France, Belgium, the Netherlands, Australia, Canada, and South Africa. Denmark, Germany, Iran, Ireland, and the Czech Republic form a smaller number of nodes within the yellow-colored network.

In summary, the high number of co-author linkages between institutions and countries, particularly observed with Centers for Disease Control and Prevention and Global Cancer Initiative in the USA,

underscores the value of collaborative partnerships in advancing research agendas and addressing complex challenges.

5. Co-occurrence analysis

In this section, we provide a comprehensive exploration of the analyses conducted on the co-occurrences of diverse keywords within the published biomedical trait-based human identification research articles present in the Web of Science (WoS) database.

5.1. Author keyword co-occurrence analysis

This subsection delves into the keyword co-occurrences analysis employed by authors in their research articles focused on biomedical

Table 4
Key countries (P: Publications, L: Links, TLS: Total Link Strength).

Rank	Country	P	L	TLS
1	England	36	23	76
2	USA	84	20	68
3	France	15	16	50
4	Canada	22	12	43
5	Australia	17	12	43
6	Netherlands	9	12	42
7	South Africa	7	10	40
8	Spain	12	10	38
9	Belgium	7	9	37
10	Slovenia	4	9	36
11	China	54	14	26
12	India	17	12	16
13	Italy	18	9	16

Table 5
Top keywords (P: Publications, L: Links, TLS: Total Link Strength).

Rank	Keyword	P	L	TLS
1	Biomedical Monitoring	24	27	98
2	Feature Extraction	18	31	77
3	Wearable Sensors	15	22	68
4	Computer Vision	16	23	62
5	Machine Learning	19	26	57
6	Activity Recognition	10	21	52
7	Deep Learning	16	21	39
8	Sensors	9	21	38
9	Accelerometers	8	16	37
10	Human Activity Recognition	10	15	29
11	Support Vector Machines	6	15	28
12	Internet Of Things	4	10	20
13	Biomedical Signal Processing	6	10	13

trait-based human identification in the last decade. Leveraging the VoSviewer search, a total of 1328 keywords were collected. Employing a fractional counting approach with a requirement of at least 3 occurrences per keyword, co-occurrences among these keywords were examined. This criterion resulted in 71 keywords meeting the requirement, with 58 forming the most extensive interconnected network. Table 5 lists the top 10 co-occurring keywords with the highest TLS values within this network. The table encapsulates the foremost thirteen keywords frequently cited by researchers in their biomedical trait-based human identification research articles featured in WoS. For instance, the keyword 'Biomedical Monitoring' accumulates 24 occurrences, aligned with 27 keyword linkages, culminating in a co-occurrence TLS of 98.

The keyword co-occurrence grids are depicted in Fig. 14. The most prominent node in the red-colored co-occurrence grid is the top-ranked keyword 'Biomedical Monitoring', which co-occurs with terms like 'Internet of Things' (rank 12). Within the green-colored network, significant keywords include 'Feature Extraction' (rank 2), 'Wearable Sensors' (rank 3), 'Activity Recognition' (rank 6), 'Sensors' (rank 8), 'Accelerometers' (rank 9), 'Support Vector Machines' (rank 11), and 'Biomedical Signal Processing' (rank 13). Similarly, the red-colored network includes the other three top TLS keywords: 'Machine Learning' (rank 5), 'Deep Learning', and 'Computer Vision' (rank 4). These visualizations offer valuable insights into the interconnectedness and research trends associated with keywords in the field of biomedical trait-based human identification.

This finding suggests the presence of published articles wherein authors have not mentioned any other keywords related to biomedical trait-based human identification research. It could also imply that certain published articles feature only those keywords from biomedical trait-based human identification research that have occurred less than 10 times themselves. Consequently, such keywords are not considered in the present analysis and are excluded from the count of co-occurring keywords.

Table 6
Leading researchers by citation impact (P: Publications, C: Citations, L: Links, TLS: Total Link Strength).

Rank	Researcher	Country	P	C	L	TLS
1	Zhang, Z	China	3	108	2	2
2	Zhang, Wei	China	2	36	2	2
3	Chen, H	China	2	15	3	3
4	Wang, W	China	2	11	3	3

6. Citation analysis

In this section, we present the networks based on citations within the field of biomedical trait-based human identification research.

6.1. Author-based citation analysis

In this subsection, we delve into a citation analysis of authors who have contributed to biomedical trait-based human identification research in the last decade. By employing VoSviewer, a total of 1466 authors were identified. The citations received by these authors underwent analysis using a criterion of at least 2 publications and 2 citations per author. Publications involving more than 25 authors were not taken into account. Out of these parameters, 74 authors met the criteria. Fig. 15 illustrates the network of citations within the international biomedical trait-based human identification research community. Interestingly, the most extensive interconnected network is comprised of four authors, presented in a red-colored grid.

Table 6 highlights the top four cited authors from this connected set, showcasing their notable contributions to biomedical trait-based human identification research. The table provides insights into the authors' citation counts and the number of citation links they have received, signifying the unique researchers who cited their works in WoS. Of significance is the prominence of Chinese researchers, with Zhang, Z (rank 1) and Zhang, Wei (rank 2) leading the list with 108 and 32 citation counts, both possessing an equal TLS score of 2. Following closely are Chen, H (rank 3) and Wang, W, each accumulating 15 and 11 citation counts, and sharing the same TLS score of 3.

6.2. Country-based citation analysis

In this section, we examine how various countries have contributed to the field of biomedical trait-based human identification research over the past decade. Using VoSviewer, we identified a total of 67 nations involved in this research area. We then analyzed the citations associated with these countries, with a requirement of at least 2 published documents and 2 citations per nation. To maintain focus, we excluded publications involving more than 25 countries as co-authors. As a result, 46 countries met these criteria and formed a connected network of 26 nations. The top ten most cited nations from this group, indicated by their high TLS values, are presented in Table 7.

The table provides insights into the top 13 countries with the highest citations, determined by TLS values, in the field of biomedical trait-based human identification research. For instance, the USA emerges as the leader in the list with 3312 international citation links and a total link strength of 12 while England has authored 36 WoS papers in the field of biomedical trait-based human identification research, which have collectively accumulated 1907 citations.

Fig. 16 illustrates the citation network within the context of biomedical trait-based human identification research across nations. The figure unveils two prominent networks represented by nodes and links in distinct colors: green and red. The red network consists of nations with higher citation metrics, including China, USA Colombia, Belgium, South Korea, and more. Contrary, the green network encompasses nations with comparatively lower citation metrics, such as England, Turkey, India, Malaysia, and Taiwan, among others. The yellow network predominantly features European countries like France, Italy,

Fig. 14. Author keywords co-occurrence network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
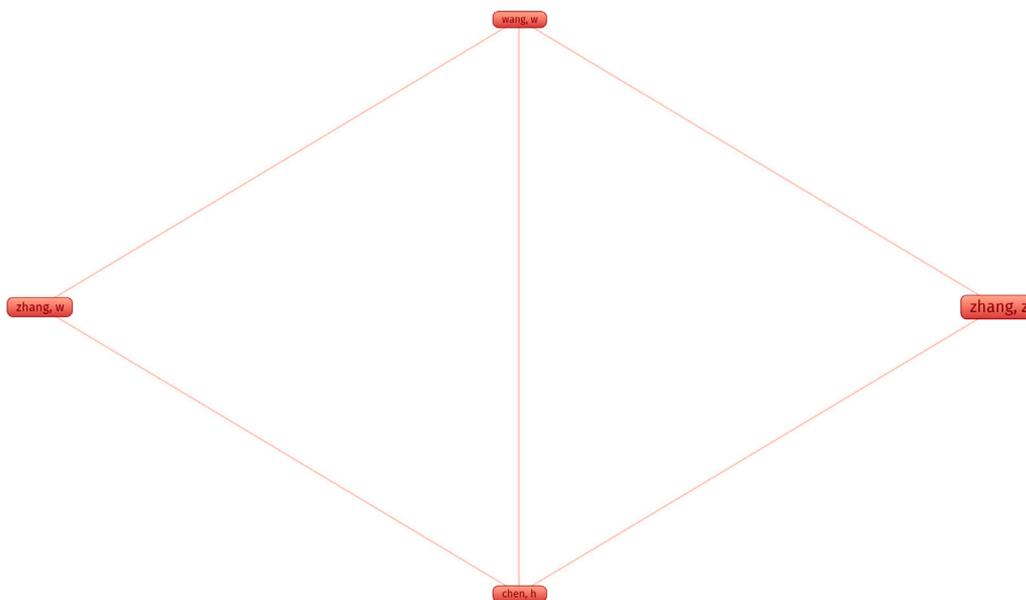
Fig. 15. Researchers citation network in the field of biomedical trait-based human identification.

Switzerland, and Finland, while the blue network includes Germany, Greece, Denmark, and Luxembourg. Lastly, the purple network involves nations such as Egypt, Saudi Arabia, and Poland.

6.3. Document-based citation analysis

In this subsection, we present a citation analysis focusing on countries within the field of biomedical trait-based human identification research articles in the last decade. Employing VoSviewer, we identified a total of 326 such publications. The citations associated with these articles underwent scrutiny, adopting a threshold of at least 2 citations per publication. This criterion was met by 270 sources, and 4 documents comprised the largest interconnected set, as detailed in Table 8. The table also offers details regarding the citations received by these

articles from other publications in the field of biomedical trait-based human identification published in WoS. For instance, the paper titled 'Physical activity recognition by smartphones: a survey' [52] received a total of 71 citations.

Fig. 17 visualizes the citation-based networks of biomedical trait-based human identification documents published in WoS. The distinct colored nodes and linkages depict co-citations and offer insights into the interconnectedness of these research articles.

6.4. Organizational citation analysis

In this subsection, we present a citation analysis focusing on organizations involved in the realm of biomedical trait-based human identification research over the past two decades. Through the use of
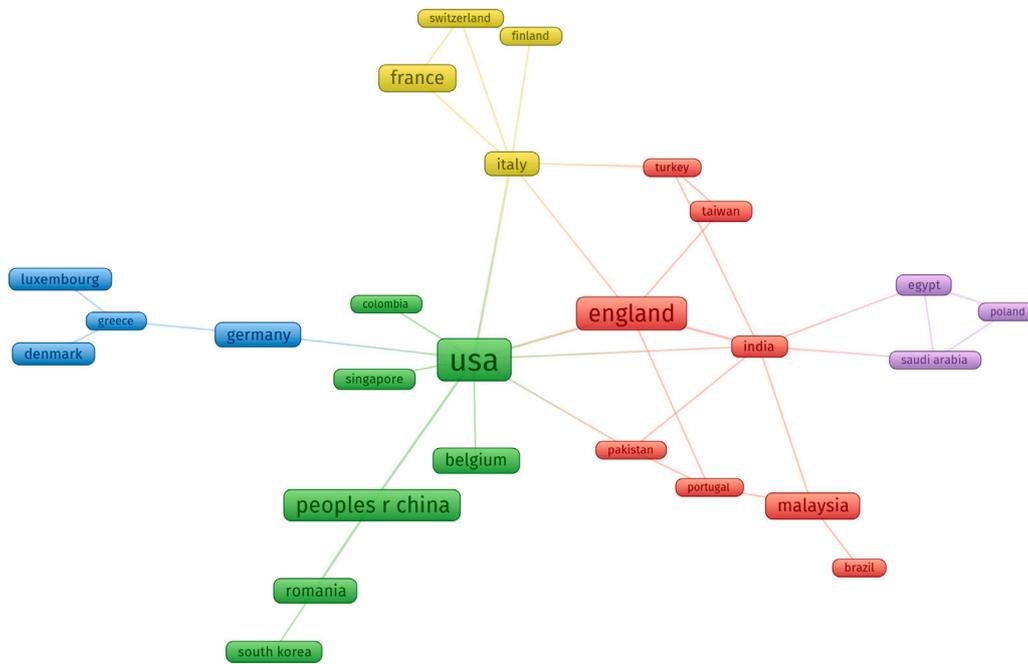
Fig. 16. Countries citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
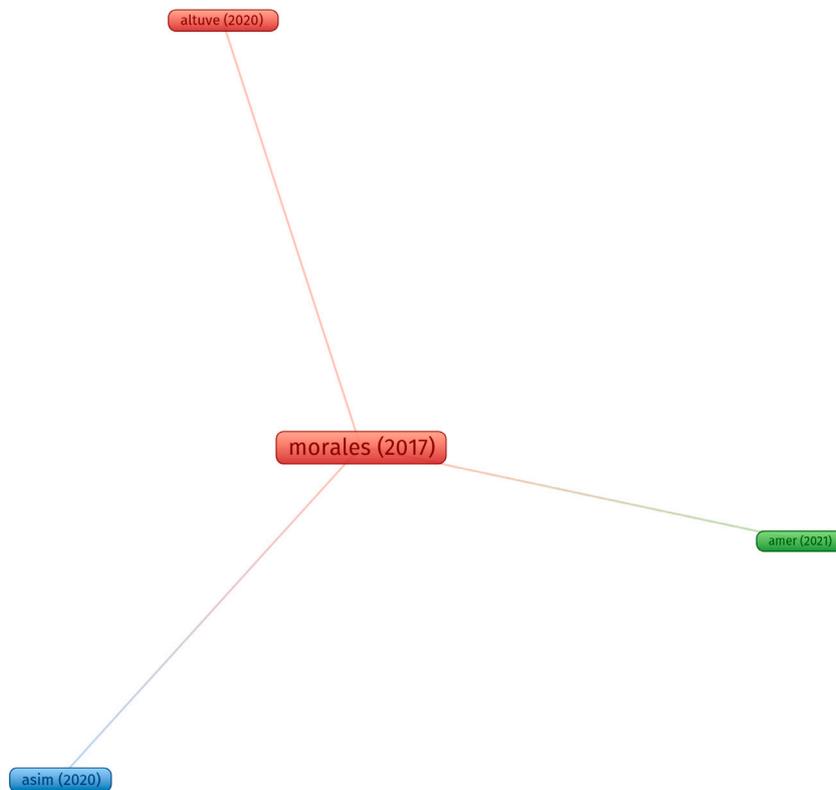
Fig. 17. Document citation network in the field of biomedical trait-based human identification.

VoSviewer, we identified a total of 614 such organizations. Employing a threshold requiring a minimum of 2 publications and 2 citations per organization, we proceeded to analyze the citations attributed to these institutions. We excluded documents co-authored by more than 20 organizations to ensure precision. Overall, our analysis involved 116 organizations that met these criteria, resulting in 4 interconnected sources forming the largest set.

Table 9 showcases the top four organizations globally with the highest citation-based total link strength (TLS) scores within the field of biomedical trait-based human identification research. At the top of the list is 'King's College London, England', with 3 papers, 375 citations, 2 inter-institutional citation linkages, and a TLS of 2. Following closely is 'MIT, USA', also with 3 papers, 38 citations, 2 inter-institutional citation linkages, and a TLS of 2. Further down the list, two Indian

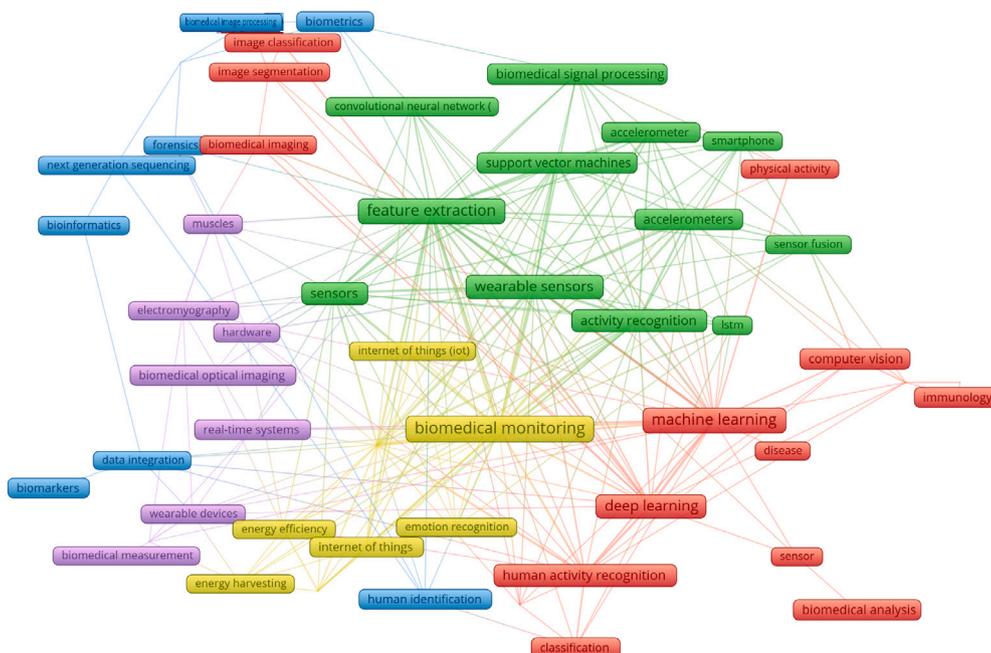**Fig. 18.** Organization citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7
Prominent countries by citation impact (P: Publications, C: Citations, L: Links, TLS: Total Link Strength).

Rank	Country	P	C	L	TLS
1	USA	84	3312	9	12
2	England	36	1907	5	7
3	Peoples R China	54	1603	2	4
4	France	15	1061	2	2
5	Malaysia	2	886	3	3
6	Belgium	7	701	1	1
7	Germany	18	684	2	2
8	Romania	2	666	2	3
9	Italy	18	532	6	7
10	Denmark	7	418	1	1
11	Luxembourg	2	344	1	1
12	South Korea	16	276	1	1
13	India	17	261	7	8

organizations, 'Malaviya National Institute of Technology', and 'Swami Keshvanand Institute of Technology Management & Gramothan', each have 2 papers, 7 citations, 2 inter-organizational citation linkages, and a TLS of 2.

Fig. 18 illustrates the global organizational citation-based connections in the field of biomedical trait-based human identification. Different colors denote distinct citation networks. Notably, two distinct clusters are evident, each composed of two nodes. The green network consists of 'Swami Keshvanand Institute of Technology Management, India' (citation TLS rank 4), and 'MIT, USA' institution (citation TLS rank 2). Conversely, the red network encompasses 'Malaviya National Institute of Technology, India' (citation TLS rank 3), and 'King's College London, England' (citation TLS rank 1).

6.5. Source-based citation analysis

Within this subsection, we delve into a citation analysis of sources that have contributed to the field of biomedical trait-based human identification research over the past two decades. Our VoSviewer search yielded a total of 228 such sources. Employing a threshold stipulating a minimum of 2 published documents and 2 citations per source, we examined the citations attributed to these sources. Among them, only 44 sources met these criteria, with 6 forming the most interconnected set of sources. The table found in Table 10 highlights the sources garnering the highest total link strength (TLS) values within this connected set.

At the top of this list is 'Biocybernetics and Biomedical Engineering', which has contributed 5 articles to the realm of biomedical trait-based human identification research. These articles have collectively 201 citations from various other journals within the Web of Science (WoS). Among these referencing sources, only a select few satisfy the inclusion criteria set forth in this study, mandating a minimum of 2 published documents and 2 citations per source. Consequently, the combined citations directed towards 'Biocybernetics and Biomedical Engineering' from these shortlisted and linked journals tally up to 2, as visually depicted within the network in red. Noteworthy peers in this red-hued network encompass 'IEEE Sensors Journal' (TLS 2) and 'Signal Image and Video Processing' (TLS 1).

Emerging as the second most notable, 'IEEE Access' boasts a remarkable citation-based TLS score of 2 in comparison to all other WoS sources. This prominence is depicted in the source citation network map (depicted in Fig. 19), where 'IEEE Access' occupies a central node. Alongside it, the green-colored network incorporates other journals like 'IEEE Transactions On Biomedical Circuits and Systems' (TLS 2) and 'IEEE Transactions On Instrumentation and Measurement' (TLS 1).

Overall the citation analysis provides insights for future researchers to build their future research strategies and collaborations that amplify

Table 8

Key articles with maximum citation links (C: Citations, L: Links).

Rank	Article Title	Authors	Year	Journal	C	L
1	Physical activity recognition by smartphones: a survey [52]	Jafet Morales; David Akopian	2017	Biocybernetics and Biomedical Engineering	71	3
2	Context-Aware Human Activity Recognition (CAHAR) in-the-Wild Using Smartphone Accelerometer [53]	Yusra Asim; Muhammad Awais Azam; Muhammad Ehatisham-ul-Haq; Usman Naeem; Asra Khalid	2020	IEEE Sensors Journal	18	1
3	Human activity recognition using improved complete ensemble EMD with adaptive noise and long short-term memory neural networks [54]	Miguel Altuve; Paula Lizarazo; Javier Villamizar	2020	Biocybernetics and Biomedical Engineering	11	1
4	A Localized Learning Approach Applied to Human Activity Recognition [55]	Ahmed Youssef Ali Amer; Jean-marie Aerts; Bart Vanrumste; Stijn Luca	2021	IEEE Intelligent Systems	3	1
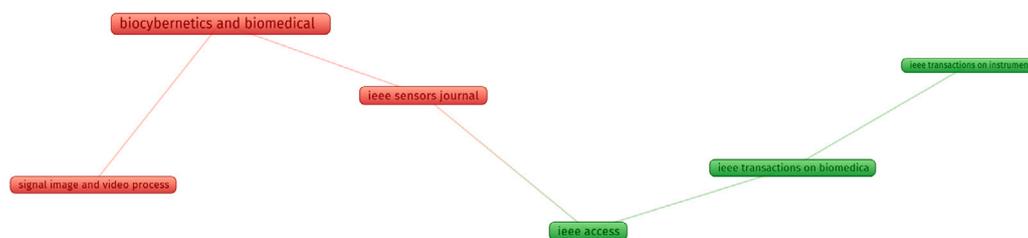
Fig. 19. Publication source citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
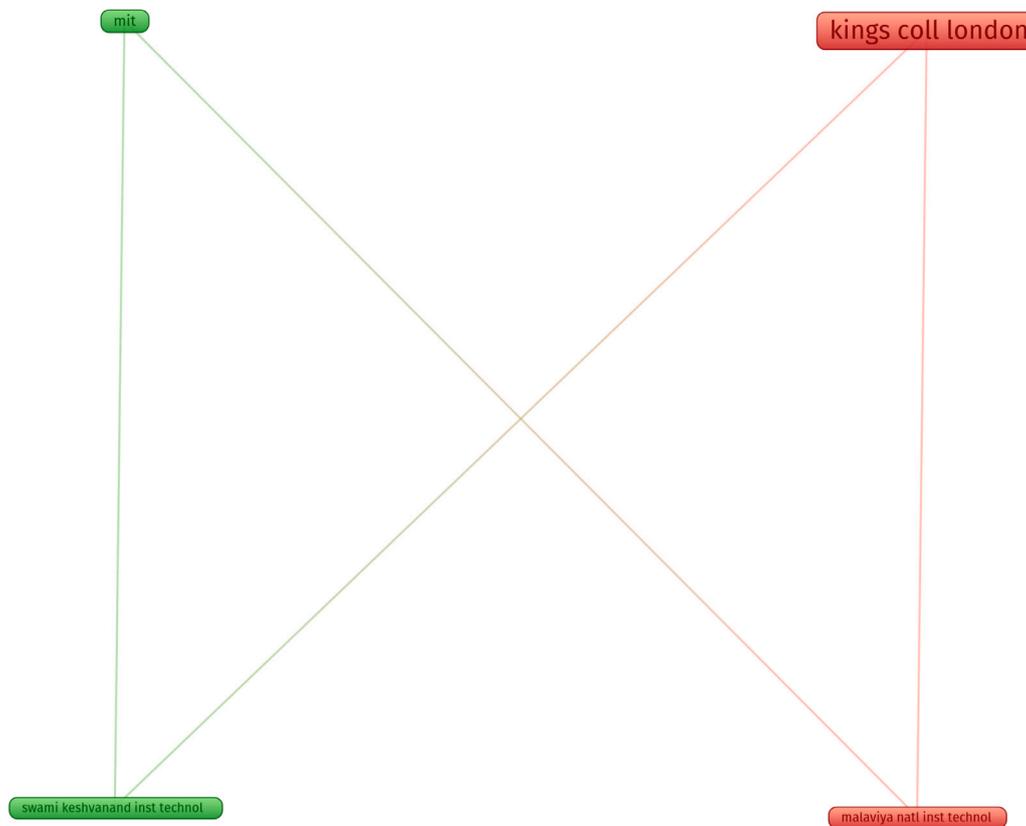
Table 9

Leading institutions by citation impact (P: Publications, C: Citations, L: Links, TLS: Total Link Strength).

Rank	Institution	P	C	L	TLS
1	King College London, England	3	375	2	2
2	MIT, USA	3	38	2	2
3	Malaviya National Institute Technology, India	2	7	2	2
4	Swami Keshvanand Institute of Technology Management & Gramothan, India	2	7	2	2

Table 10

Prominent sources by citation impact (P: Publications, C: Citations, L: Links, TLS: Total Link Strength).

Rank	Source	P	C	L	TLS
1	Biocybernetics and Biomedical Engineering	5	201	2	2
2	IEEE Access	13	126	2	2
3	IEEE Sensors Journal	8	114	2	2
4	IEEE Transactions On Biomedical Circuits and Systems	5	68	2	2
5	Signal Image and Video Processing	2	57	1	1
6	IEEE Transactions On Instrumentation and Measurement	3	12	1	1

the reach and influence of their research outcomes. Firstly, the significance of individuals who have achieved high citation counts and are linked to multiple researchers underscores the importance of individual contributions to scholarly impact. Secondly, the presence of countries with high citation-based TLS values indicates the value of international collaboration in research endeavors, suggesting that researchers may

benefit from forging partnerships with institutions from these countries to enhance the visibility and impact of their work. Lastly, the recognition of institutions with high citation counts highlights the importance of institutional affiliations in driving research visibility and recognition.

7. Co-citation analysis

In this section, we present the networks based on co-citations among authors, documents, and sources within the domain of biomedical trait-based human identification research spanning the last two decades.

7.1. Co-citation analysis of cited authors

This subsection conducts an analysis of co-citations among authors in the realm of biomedical trait-based human identification research throughout the past decade. The VoSviewer search yielded a total of 13,261 cited authors, representing the first authors of published articles. Employing the fractional counting method, we scrutinized the co-citations among these authors, setting a threshold of a minimum of 5 citations for inclusion. From the pool of cited authors, only 146 met the criterion of being cited 20 times or more. The table below (Table 11) presents the top ten authors with the highest Total Link Strength (TLS) values. This comprehensive compilation furnishes insights into highly co-cited authors within the domain of biomedical trait-based human identification, encompassing their names, affiliated countries, citation counts (individual citing document count), the number of co-cited authors, and the cumulative strength of each co-cited link (TLS). Notably, the list is predominantly occupied by three researchers from China, followed by two authors each from the Czech Republic, Italy, and Japan. Furthermore, this list features one author each from Australia, Thailand, Spain, and the USA.

Fig. 20 illustrates the co-citation network map within the context of biomedical trait-based human identification research authors. The figure highlights the top thirteen co-cited authors with notable TLS

Fig. 20. Author co-citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 11
Leading researchers by co-citation impact (C: Citations, L: Links, TLS: Total Link Strength).

Rank	Researcher	Country	C	L	TLS
1	Chen, X	China	43	35	229
2	Kuramoto, T	Japan	11	5	209
3	Liska, F	Czech Republic	7	5	161
4	Phinyomark, A	Thailand	17	24	146
5	Mashimo, T	Japan	5	5	125
6	Pravenec, M	Czech Republic	5	5	125
7	Naik, Gr	Australia	10	18	108
8	Jain, Ak	USA	14	31	100
9	Stanyon, R	Italy	10	2	100
10	Dumas, F	Italy	9	2	99
11	Zhang, Y	China	15	34	94
12	Li, Y	China	11	37	90
13	Gomez, O	Spain	8	9	80

values. In the green-colored network, prominent nodes include authors such as Chen X (China) and Li Y (China). The blue network prominently features authors like Kuramoto *T* (Japan), Mashimo *T* (Japan), Pravenec M (Czech Republic), and Liska F (Czech Republic) as significant nodes. Meanwhile, the cyan-colored network is characterized by important nodes like Phinyomark A (Thailand), Zhang Y (China), and Naik Gr (Australia).

7.2. Co-citation analysis of cited references

This subsection introduces a co-citation analysis of research papers on biomedical trait-based human identification, as cited by documents within the WoS database over the past two decades. The VoSviewer search yielded a collection of 16,274 cited biomedical trait-based human identification research papers. We conducted an analysis of these papers using the fractional counting method, considering papers with at least 4 citations for our study. From this pool, only 57 documents met the criterion of being cited 20 times or more, and out of these, 35 formed the most extensive interconnected network. Table 12 presents the top ten cited documents with the highest TLS values. This comprehensive compilation features documents that exhibit the highest co-cited TLS values, stemming from citations within biomedical trait-based human identification-related publications over recent decades.

As an illustration, the document ranked highest in terms of TLS (Ronao and Cho [56]) possesses 9 citations and a TLS of 33. Similarly, the document referenced by (Ordóñez and Roggen [57]) has a TLS of 29 and has been cited 7 times.

Fig. 21 illustrates the co-citation network maps of research documents focused on biomedical trait-based human identification. The figure highlights the most influential co-cited documents with high TLS values, including references like Ronao and Cho [56], Ordóñez and Roggen [57], Lara and Labrador [58], Hassan et al. [59], Wang et al. [60], Anguita et al. [61], and Wang et al. [62], which are connected within the red-colored co-cited network. In addition, are key nodes within the blue and green networks, contributing significantly to their structure.

7.3. Co-citation analysis of cited sources

This subsection undertakes an analysis of co-citations among journals that have published research on biomedical trait-based human identification within the last decade. Through the VoSviewer search, a total of 5655 journals were identified as being cited in these research papers. To emphasize meaningful co-citations, a threshold of at least 20 citations per journal was employed. This refined the list to 118 journals that were frequently co-cited.

Table 13 showcases the top ten co-cited sources with the highest TLS values. This table ranks journals based on their co-citation TLS values, which reflect their interconnectedness with other co-cited journals. The table provides journal names, the number of citations received from the studied papers, the count of individual co-cited journals they are connected to (links), and the cumulative strength of these linkages (TLS).

Fig. 22 visually represents the co-citation-based networks among various publishing sources in the Web of Science (WoS), categorized by distinct colors. Notably, the green network prominently features top co-citation TLS journals such as Proceedings of the National Academy of Sciences, Nature, PLOS, Science, Nature Genetics, and Scientific Reports-UK. Additionally, a separate co-cited network is depicted in yellow, encompassing sources like Molecular & Cellular Proteomics, Journal of Proteome Research, Nucleic Acids Research, Cell, Analytical Chemistry, and Proteomics. The red network comprises significant

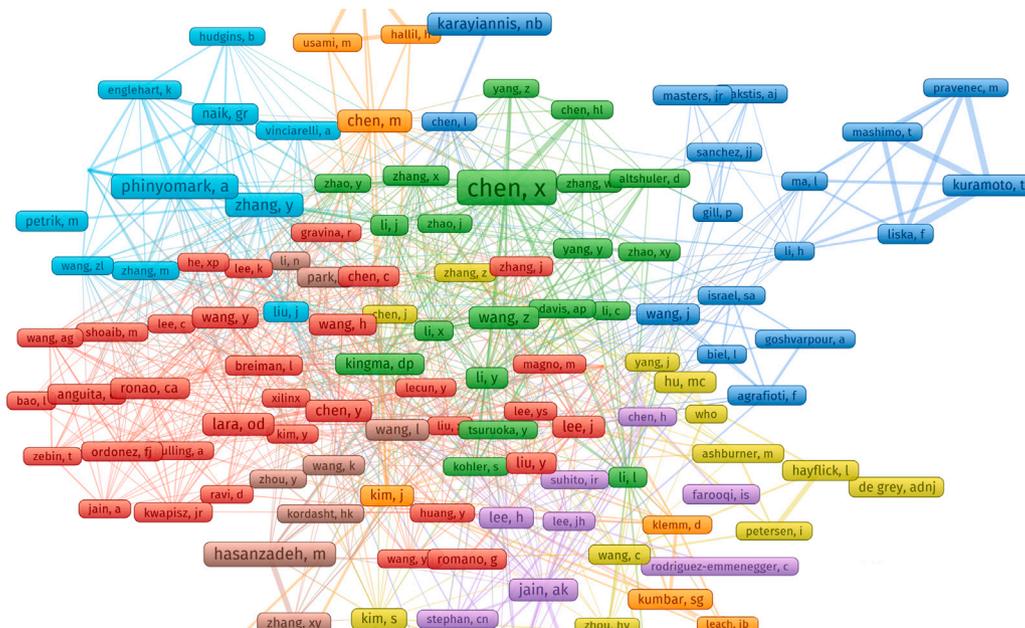**Fig. 21.** Cited reference co-citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 12
Highly Co-cited Articles (P: Publications, C: Citations, L: Links, TLS: Total Link Strength).

Rank	Title	Authors	Year	Journal	C	L	TLS
1	Human activity recognition with smartphone sensors using deep learning neural networks [56]	Charissa Ann Ronao; Sung-Bae Cho	2016	Expert Systems with Applications	9	16	33
2	Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition [57]	Francisco Javier Ordóñez; Daniel Roggen	2016	Sensors	7	16	29
3	A Survey on Human Activity Recognition using Wearable Sensors [58]	Oscar D. Lara; Miguel A. Labrador	2012	IEEE Communications Surveys & Tutorials	11	18	25
4	A robust human activity recognition system using smartphone sensors and deep learning [59]	Mohammed Mehedi Hassan; Md. Zia Uddin; Amr Mohamed; Ahmad Almogren	2018	Future Generation Computer Systems	6	14	23
5	A Comparative Study on Human Activity Recognition Using Inertial Sensors in a Smartphone [60]	Aiguo Wang; Guilin Chen; Jing Yang; Shenghui Zhao; Chih-Yung Chang	2016	IEEE Sensors Journal	5	13	21
6	A public domain dataset for human activity recognition using smartphones [61]	Anguita, Davide; Ghio, Alessandro; Oneto, Luca; Parra Perez, Xavier; Reyes Ortiz, Jorge Luis	2013	European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning	5	14	20
7	Deep learning for sensor-based activity recognition: A survey [62]	Jindong Wang; Yiqiang Chen; Shuji Hao; Xiaohui Peng; Lisha Hu	2019	Pattern Recognition Letters	4	10	17
8	Adam: A Method for Stochastic Optimization [63]	Diederik P. Kingma; Jimmy Ba	2015	International Conference for Learning Representations	10	13	16
9	A Survey of Online Activity Recognition Using Mobile Phones [64]	Muhammad Shoaib; Stephan Bosch; Ozlem Durmaz Incel; Hans Scholten; Paul J.M. Havinga	2015	Sensors	4	12	16
10	ECG to identify individuals [65]	Steven A. Israel; John M. Irvine; Andrew Cheng; Mark D. Wiederhold; Brenda K. Wiederhold	2005	Pattern Recognition Letters	5	5	15

nodes formed by sources like the Journal of Biological Chemistry and Nature.

The Co-citation analysis highlights the potential platforms such as certain journals that have attained high co-citation TLS values, facilitating interdisciplinary discourse and knowledge dissemination. Therefore, future researchers may consider collaborating with highly co-cited individuals and targeting reputable journals to enhance the visibility and impact of their research outcomes.

8. Temporal analysis and burst detection

In this section, we reveal the results obtained from analyzing the timeline and detecting bursts using the CiteSpace tool. The timeline

Fig. 22. Cited publication source co-citation network in the field of biomedical trait-based human identification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 13
Prominent Co-cited Sources (C: Citations, L: Links, TLS: Total Link Strength).

Rank	Sources	C	L	TLS
1	Proceedings of the National Academy of Sciences	209	94	9184
2	Nature	233	114	8076
3	Plos One	158	115	7432
4	Molecular & Cellular Proteomics	56	56	5655
5	Journal of Proteome Research	63	56	5406
6	Science	179	111	5241
7	Nature Genetics	102	86	5174
8	Scientific Reports-UK	112	114	5101
9	Nucleic Acids Research	160	86	4128
10	Cell	103	87	4001
11	Analytical Chemistry	107	92	3871
12	Journal of Biological Chemistry	91	88	3820
13	Proteomics	43	48	3777

review analysis sheds light on the evolving research trends in biomedical trait-based human identification from 2003 to 2023. On the other hand, burst detection analyses pinpoint documents and keywords that witnessed sudden spikes in citations within certain time periods. These analyses not only highlight the intensity of such bursts but also help us understand the relative importance attributed by the research community to specific documents and keywords over time.

8.1. Temporal review analysis

The results of the timeline analysis, conducted using the CiteSpace tool, unveil the evolution of research trends in biomedical trait-based human identification from 2003 to 2023. These findings are visualized in Fig. 23, where six distinct topic clusters are depicted in different colors.

Notably, the research community's attention has prominently gravitated towards the topic of biomedical monitoring during the latter half of the second decade (2010–2023). Prior to 2005, this area showed comparatively less significance. In contrast, topic clusters like system biology and vaginal cancer have consistently maintained researchers' interest throughout the initial decade. Over the last five years, emerging trends have been observed in areas such as medical image processing and biomedical analysis, indicating their growing importance. Furthermore, the realm of regenerative medicine remains a relatively less explored territory, suggesting an open avenue for future investigation within the context of biomedical trait-based human identification.

8.2. Keyword burst analysis

This subsection provides an in-depth account of the burst detection analysis conducted on biomedical trait-based human identification keywords over the last decade. The findings are presented in Table 14, which outlines the top 15 keywords ranked by their burst strengths in descending order. Notably, during specific time periods, certain keywords experienced sudden surges in citation activity.

For instance, the keywords 'biomedical monitoring', 'machine learning', and 'feature extraction' exhibited robust burst strengths of 2.51, 1.87, and 1.67, respectively, within the time frames 2020–23, 2019–23, and 2020–23. Similarly, keywords like 'deep learning', 'activity recognition', 'human activity recognition', and 'wearable sensors' demonstrated significant peaks in interest over the past 3–4 years, with burst strengths of 1.46, 1.44, 1.33, and 1.21, respectively.

The burst detection analysis also unveiled sustained bursts for specific keywords. Notably, 'cancer', 'biomedical applications', and 'drug delivery' showcased bursts that spanned from the beginning of the second decade in 2011 up to 2017, with respective strengths of 1.16, 0.98, and 0.87. Notably, the keyword 'identification' displayed bursts across the longest period, ranging from 2006 to 2016.

These findings provide a compelling indication of the shifting research focus within the biomedical trait-based human identification community, highlighting the growing prominence of areas such as machine learning, deep learning, and wearable sensors.

8.3. Reference burst analysis

This subsection provides an insightful analysis of burst detection conducted on cited biomedical trait-based human identification research documents spanning two decades. The findings are presented in Table 15, listing the top 15 research articles ranked by their burst
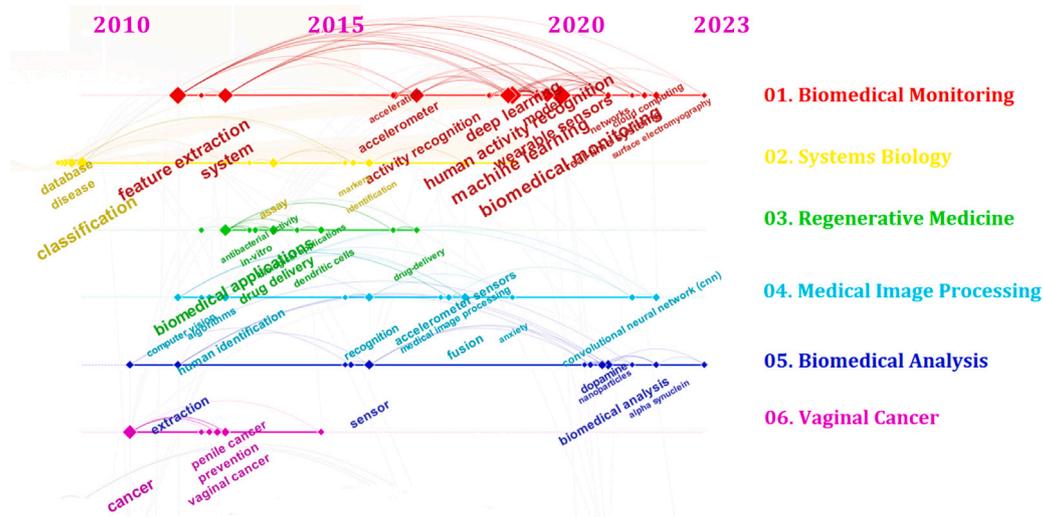
Fig. 23. Temporal evolution of keywords in biomedical trait-based human identification research.

Table 14
Prominent keywords with high keyword burst strength.

Rank	Keywords	Year	Strength	Start	End	2003–2023
1	Biomedical monitoring	2020	2.51	2020	2023	
2	Machine learning	2019	1.87	2019	2023	
3	Feature extraction	2020	1.67	2020	2023	
4	Deep learning	2019	1.46	2019	2023	
5	Activity recognition	2020	1.44	2020	2021	
6	Human activity recognition	2019	1.33	2019	2023	
7	Wearable sensors	2020	1.21	2020	2023	
8	Cancer	2011	1.16	2011	2013	
9	Biomedical applications	2014	0.98	2014	2017	
10	Drug delivery	2014	0.87	2014	2015	
11	Biomedical analysis	2021	0.71	2021	2023	
12	Fusion	2018	0.69	2018	2019	
13	Classification	2019	0.68	2019	2020	
14	Identification	2006	0.54	2006	2016	
15	Biomedical image processing	2004	0.28	2004	2005	

strengths in descending order. Notably, the article authored by Ordóñez and Roggen [57] exhibited the highest burst strength of 0.95 over a three-year period, specifically from 2016 to 2019. Following closely, the work of Hassan et al. [59] achieved the second-highest burst strength of 0.79 during the years 2018–2019. A noteworthy observation emerges from a cluster of seven articles authored by Castle et al. [66], Denny et al. [67], Arbyn et al. [68], Bosch et al. [69], Canfell et al. [70], Doorbar et al. [71], and Cuzick et al. [72], each attaining a uniform citation burst strength of 0.69. Furthermore, the work of Eppig et al. [73] displayed a sustained citation burst strength of 0.49, spanning the longest period from 2011 to 2023. These burst detection results reveal how interest in particular research articles has changed over time. They provide insights into the shifts in research focus within the field of biomedical trait-based human identification.

In a nutshell, the burst strength analysis offers valuable insights for future researchers, highlighting areas of emerging interest and influential publications within the field. Firstly, the significant burst strength observed for the keyword associated with a specific area within the biomedical field during a particular time period highlights a surge in research activity and interest in this domain. This suggests that there may be emerging trends, technological advancements,

or pressing challenges related to this topic that warrant further investigation and exploration. Secondly, the publication achieving the highest burst strength during a specific time frame indicates a period of notable attention and impact within the field. Researchers may find it valuable to closely examine such influential publications, as they likely contain seminal insights, methodologies, or findings that have influenced subsequent research endeavors. Analyzing these influential works can provide valuable guidance for future research directions, methodologies, and theoretical frameworks. By leveraging these insights, researchers can strategically align their research focus and contribute to advancing knowledge and innovation in relevant domains.

9. Conclusions and future outlook

This study conducts a thorough analysis of various aspects within the field of biomedical trait-based human identification research over the past decade. The investigation starts by examining annual publications, publication types, sources, organizations, researchers, countries, and thematic domains. These analyses are then further explored using co-authorship, co-occurrence, citation, and co-citation perspectives.

Table 15
Prominent references with high keyword burst strength.

Rank	References	Year	Strength	Start	End	2010–2023
1	Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition [57]	2016	0.95	2016	2019	
2	A robust human activity recognition system using smartphone sensors and deep learning [59]	2018	0.79	2018	2019	
3	A microfluidic paper-based colorimetric device for the visual detection of uric acid in human urine samples [74]	2021	0.69	2021	2021	
4	Introduction of human papillomavirus DNA screening in the world: 15 years of experience [66]	2012	0.69	2014	2023	
5	Human papillomavirus, human immunodeficiency virus and immunosuppression [67]	2012	0.69	2014	2023	
6	Evidence regarding human papillomavirus testing in secondary prevention of cervical cancer [68]	2012	0.69	2014	2023	
7	Reframing cervical cancer prevention. Expanding the field towards prevention of human papillomavirus infections and related diseases [69]	2012	0.69	2014	2023	
8	Modeling preventative strategies against human papillomavirus-related disease in developed countries [70]	2012	0.69	2014	2023	
9	The biology and life-cycle of human papillomavirus [71]	2012	0.69	2014	2023	
10	New technologies and procedures for cervical cancer screening [72]	2014	0.69	2014	2023	
11	Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges [75]	2017	0.63	2017	2023	
12	Human activity recognition with smartphone sensors using deep learning neural networks [56]	2016	0.63	2016	2019	
13	Novel enzymatic graphene oxide based biosensor for the detection of glutathione in biological body fluids [76]	2022	0.49	2022	2023	
14	The Mouse Genome Database (MGD): from genes to mice—a community resource for mouse biology [73]	2005	0.49	2011	2023	
15	A survey on activity detection and classification using wearable sensors [77]	2017	0.49	2017	2019	

The fractional counting method is used to assess co-authorship, co-citation, and co-occurrence. Additionally, the study explores timeline and burst detection outcomes to identify keywords and documents that experienced significant temporal shifts. The main findings of this study are summarized as follows:

1. Each year, over 326 publications related to biomedical trait-based human identification appear in WoS.
2. The majority of these publications are research articles (84.97%).
3. IEEE Access is the journal with the highest count of biomedical trait-based human identification-related publications (13) in WoS.
4. The Chinese Academy of Sciences (China) leads in the number of published articles (12).
5. The USA has the highest number of authors (84), followed by Chinese authors (54).
6. Engineering is the most prominent research area with the highest count of biomedical trait-based human identification-related publications (86).
7. The Science Citation Index Expanded (SCI-Expanded) contains the most WoS biomedical trait-based human identification-related publications (319).
8. The subject category 'Engineering Electrical Electronic' encompasses the highest count of WoS biomedical trait-based human identification-related publications (55).
9. Wang Xiao Y (China) holds the highest co-authorship-based TLS (16) with 16 co-author linkages.
10. Centers for Disease Control and Prevention (USA) and Global Cancer Initiative (USA) lead in co-authorship-based TLS (93) with 24 co-author linkages each.
11. England achieves the highest co-authorship-based TLS (76) with 23 other nations.
12. 'Biomedical Monitoring' has the highest co-occurrence-based TLS (98) with 27 other authors-defined biomedical trait-based human identification-related keywords.
13. Zhang Z (China) has the highest number of citations (108) with a TLS of 2, linked to 2 other researchers.
14. The USA has the highest citation-based TLS (3312), connected with 9 countries.
15. 'King's College London, England' holds the highest citation count (375) with a TLS of 2, linked to 2 institutions.
16. 'Biocybernetics and Biomedical Engineering' achieves the highest citation count (201) with a TLS of 2, linked to 5 publications.
17. Chen X (China) attains the highest co-citation TLS (229) with 35 co-citation linkages.
18. Proceedings of the National Academy of Sciences achieves the highest co-citation TLS (9184) with 94 co-citation linkages.
19. The keyword 'Biomedical monitoring' experiences the highest burst strength (2.51) during 2020–2023.

20. The publication by Ordóñez and Roggen [57] obtains the highest burst strength (0.95) during 2016–2019.

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CRediT authorship contribution statement

Nancy Girdhar: Writing – original draft, Formal analysis, Data curation. **Deepak Sharma:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Rajeev Kumar:** Writing – review & editing, Writing – original draft, Conceptualization. **Monalisa Sahu:** Software, Resources. **Chia-Chen Lin:** Writing – review & editing, Funding acquisition.

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Data availability

All data generated or analyzed during this study are included in this published article.

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