

Article

Dermatoglyphics in Forensic Science: A Bibliometric Analysis from 1976 to 2025

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ABSTRACT: Dermatoglyphics traits—including fingerprints, palmprints, and footprints—are highly specific biometric markers that serve as critical evidence for individual identification in criminal investigations. To map the intellectual trajectory of this field, we conducted a bibliometric analysis of 796 publications indexed in the Web of Science Core Collection from 1976 to 2025. Since its emergence, research output has grown substantially. While India leads in total publications (207) and citations (3579)—largely driven by highly productive institutions such as Tumkur University and Jain University—the United States maintains the highest average citations per paper (36.8). *Forensic Science International* and the *Journal of Forensic Sciences* remain the core publishing venues. Notably, A. Jain’s 1997 work on automated fingerprint recognition remains the field’s most impactful publication, while N. Hanumanthappa has emerged as the most prolific and highly cited contemporary author. Keyword analysis reveals a distinct paradigm shift: early research focused on foundational identification principles, whereas recent hotspots center on dermatoglyphics feature extraction, algorithmic optimization, and the application of novel fluorescent nanomaterials for latent fingerprint visualization. This multidisciplinary evolution highlights an urgent paradigm shift: future advancements must bridge the translational gap between laboratory innovation and practical forensic demands by improving the transparency and judicial reliability of AI-assisted fingerprint analysis, establishing standardized evaluation systems for novel nanomaterials, and ensuring analytical compatibility with downstream genomic and multi-omics workflows.

Keywords: Forensic science; Dermatoglyphics; Fingerprint; Bibliometric; Research trend

1. Introduction

The ridge patterns on human palms and soles, scientifically termed dermatoglyphics, represent one of the most stable and unique biological markers [1]. These configurations are established by the 15th week of fetal gestation and remain virtually unchanged throughout an individual’s life [2,3]. Such permanence

and individuality underpin their utility across diverse disciplines—from anthropology [4,5] and genetics [6,7] to pattern recognition [8,9]—and have solidified their status as a cornerstone of forensic science.

Despite the dominance of DNA profiling in modern forensics, traditional fingerprint analysis remains an indispensable tool for criminal identification worldwide [10]. The practice traces its roots to 19th century colonial India, where William James Herschel first employed fingerprints for identity verification [2]. Shortly thereafter, Francis Galton established the core principles of fingerprint science, including permanence, individuality, and classifiability, and described fingerprint minutiae such as ridge bifurcations and ridge endings that remain central to personal identification today [11]. These foundational theories laid the theoretical groundwork for modern fingerprint technologies and its subsequent integration into standardized forensic procedures [12].

Driven by advances in computer technology, digital image processing, and semiconductor engineering, the United States Federal Bureau of Investigation (FBI) pioneered the Automated Fingerprint Identification System (AFIS) in the second half of the twentieth century, marking the transition from manual comparison to large-scale, computer-based matching [13,14]. Today, the field is being reshaped once more by artificial intelligence. Neural networks are moving beyond simple matching [15–17], enabling autonomous fingerprint feature extraction that significantly reduces human error and increases identification accuracy.

While fingerprints often dominate forensic discourse, palmprint and footprint analysis have achieved parallel progress. In 1963, Cummins and Midlo published the seminal work *Fingerprints, Palms and Soles: An Introduction to Dermatoglyphics*, which systematically summarized the theoretical and practical knowledge of palmprints and footprints alongside fingerprints [18]. After the large-scale application of AFIS, the FBI officially launched the Next Generation Identification (NGI) database in 2014, integrating palmprint analysis with fingerprint, facial recognition, and DNA data to build a comprehensive multimodal forensic identification system [19]. Forensic podiatry emerged in Canada and the United Kingdom in the early 1970s, although targeted systematic research did not emerge until the 1990s [20]. In 2015, Kewal Krishan published a systematic review outlining the development of forensic podiatry, formally establishing it as a specialized subdiscipline of forensic science [21]. These advancements have expanded the research scope of dermatoglyphics far beyond traditional fingerprints, solidifying its status as a versatile and core technical tool in forensic investigation.

Modern research is also uncovering significant correlations between dermatoglyphics phenotypes and broader biological traits. This inquiry dates back to 1939, when Cummins reported specific palmprint abnormalities in individuals with Down syndrome [22]. Contemporary studies have since confirmed that multiple dermatoglyphics traits, such as fingerprint ridge density and footprint morphology, are closely associated with human characteristics, including sex [23–27], height [23,27], and handedness [24]. These findings suggest that dermatoglyphics can serve as powerful non-invasive biomarkers, offering new possibilities for suspect profiling and evidence collection in complex forensic scenarios. Figure 1 illustrates the milestone applications and technological breakthroughs in forensic dermatoglyphics.

Bibliometrics offers a systematic approach to exploring the intrinsic dynamics of knowledge production. By analyzing publication trends, core author networks, and shifting research themes, it quantitatively maps the evolution of scientific disciplines. Although Girdhar et al. [28] employed this approach to delineate research trajectories in the biomedical domain of human biometric identification, bibliometric investigations focusing specifically on the application of dermatoglyphics in forensic science remain limited to date. Given the rapid technological innovation characterizing dermatoglyphics research, an important question remains unresolved: whether these emerging technologies are effectively addressing practical forensic demands or primarily reflecting short-term methodological proliferation. In this context, bibliometric analysis provides a valuable framework for distinguishing transient research hotspots from genuinely transformative directions with translational and judicial relevance. Accordingly, this study presents a comprehensive bibliometric analysis based on the Web of Science (WoS) Core Collection

spanning 1877 to 2025. The objectives are threefold: (1) to map the global distribution and collaboration networks of research efforts; (2) to identify pivotal technological milestones and paradigm shifts; and (3) to delineate emerging interdisciplinary hotspots, thematic evolution patterns, and current research frontiers in the field. Importantly, this study is intended to characterize the frontier knowledge landscape of forensic dermatoglyphics within the contexts of basic science and emerging technologies, rather than to provide a comprehensive overview of routine frontline policing practices. Therefore, the analyzed literature predominantly represents studies with strong technological innovation and frontier research significance. All publications included in this analysis are compiled in Table S1 for reference.

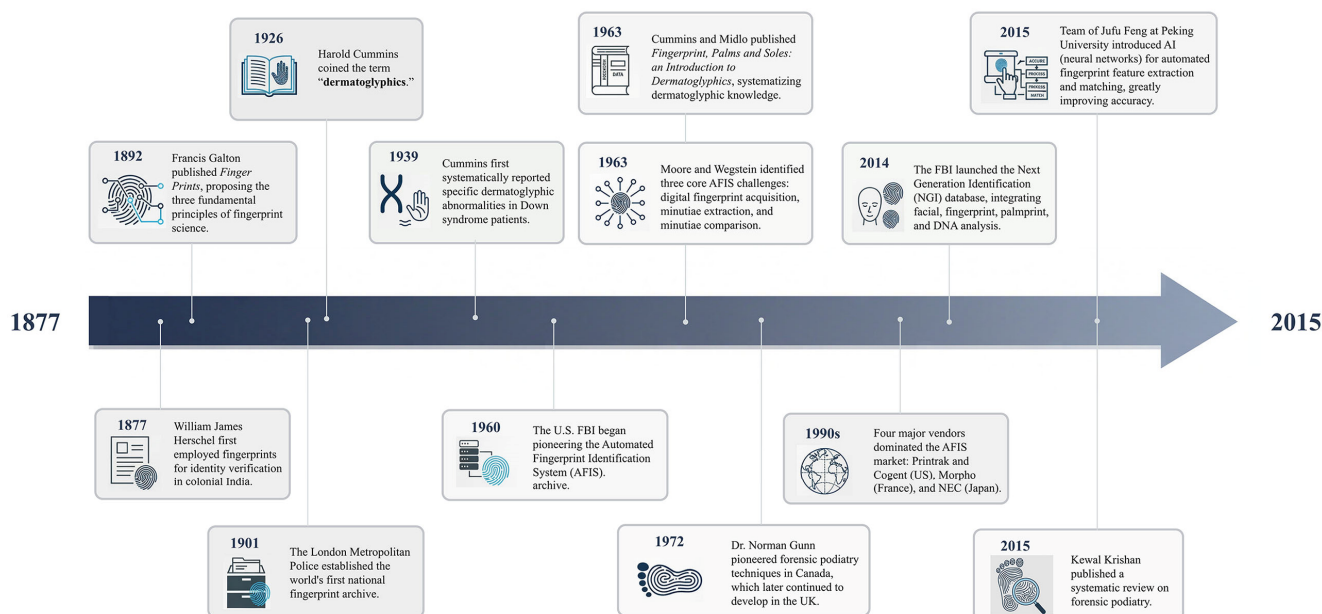


Figure 1. Milestone applications and technological advances in forensic dermatoglyphics.

2. Methods

2.1. Database and Search Strategy

We conducted a comprehensive literature search on 15 January 2026, using the WoS Core Collection, focusing specifically on the Science Citation Index Expanded (SCI) and Social Sciences Citation Index (SSCI) databases. The search strategy was formulated as follows: in the "TOPIC" field, the primary keyword group "Fingerprint* OR fingermark* OR palmprint* OR footprint* OR dermatoglyphic*". A second keyword group, "feature* OR pattern* OR ridge* OR phenotype*". The third keyword group "forensic*", was combined using the logical operator "AND". This initial search strategy yielded a total of 1716 records. We then applied additional filters, with restrictions on the publication year (≤ 2025), document type ("Article" or "Review"), and the language (English). This refinement produced 1313 relevant publications. All records were exported in plain text and Excel formats for subsequent bibliometric analyses. Two independent investigators systematically screened the titles, abstracts, keywords, and conclusions of all 1313 records to identify studies directly related to dermatoglyphics in forensic research. Studies employing metaphorical uses of the term "fingerprint", such as "DNA fingerprint" or "genomic fingerprint", were excluded to ensure the dataset represented only studies focused on epidermal ridge patterns. In cases of discrepancy or ambiguity, the full text was reviewed by a third investigator to reach a consensus. After this rigorous screening, 796 articles were retained for subsequent analyses (Figure 2, Table S1).

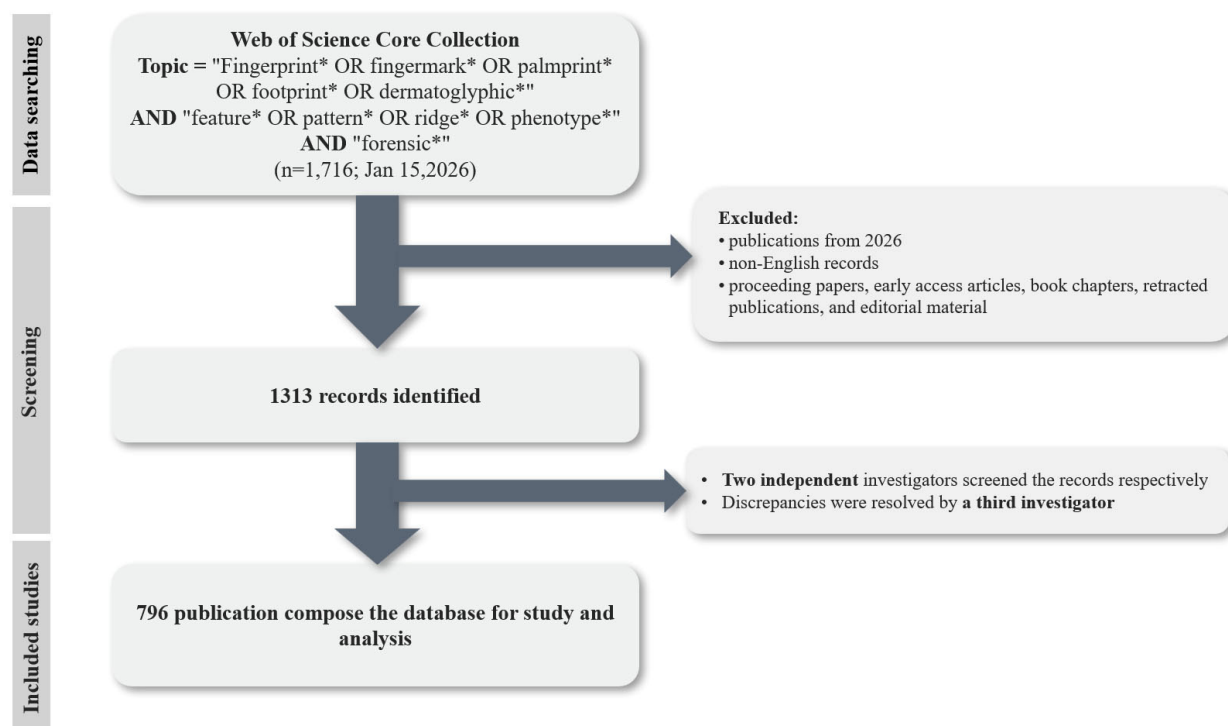


Figure 2. Publications search strategy of forensic dermatoglyphics.

2.2. Data Processing

Data cleaning of author names, countries, and keywords was performed using Python (version 3.12.6) (<https://www.python.org>, accessed on 15 January 2026) and Microsoft Excel 2019.

Author names were standardized to the full-name format, with the surname preceding the given name, following institutional conventions. For example, “Gene Badia, Manel” was reformatted as “Badia, Manel Gene”, and “Abhyankar, A” was expanded to “Abhyankar, Aditya”. For abbreviated author names, searches were conducted in Web of Science, using research topics to locate candidate Author Profiles. Author identifiers and the “Published names” listed in these profiles were then examined to verify author identity and to establish correspondences among abbreviated names, full names, and other published name variants. Name completion and merging were performed only when supported by available identifying information. When evidence was insufficient, all original name entries were retained without merging, thereby preserving information and avoiding erroneous author consolidation.

Affiliation entries listing only regional or provincial information were updated to their corresponding country. For instance, “Hong Kong” and “Taiwan” were standardized to “China”, and “North Ireland” was corrected to “United Kingdom”. All country names were normalized to capitalized format (e.g., “Algeria” was converted to “Algeria”).

Keyword analysis was based on the “Author Keywords” field. Keyword curation followed two core principles: (1) Synonyms were standardized by adopting the most widely used term. For instance, “fingerprint” and “fingerprinting” were consolidated under “fingerprint”, and “forensics” was replaced with the more precise term “forensic science”. (2) Full terms and corresponding abbreviations were standardized to a consistent format: full capitalized term followed by the abbreviation in parentheses. For example, “convolutional neural network” and “CNN” were standardized as “Convolutional Neural Network (CNN)”.

2.3. Data Analysis

The cleaned, English-language bibliographic dataset was first analyzed and visualized using VOSviewer (version 1.6.20) [29], focusing on co-occurrence patterns across multiple dimensions, including

country distribution, institutional collaborations, author networks, and author keyword co-occurrence. Subsequently, BiblioShiny (RStudio version 2024.4.2.764) [30] was used to generate bibliometric statistics and visualizations, covering publication volume, citation performance, international collaboration, core journals, and prolific authors. All analytical outputs were exported for use in downstream analyses. To map the spatial distribution of global research output and visualize international citation linkages, SCImago Graphica version 1.0.50 was employed to generate “Geographic collaboration map” and “Country Citation Chord Diagrams”. Furthermore, CiteSpace (version 6.3.1) was employed to perform keyword clustering analysis and keyword citation burst timelines, enabling the identification of research hotspots and emerging trends over time. Additional statistical processing and chart generation were performed using Microsoft Excel 2019. Collectively, these visualizations provide a comprehensive overview of the thematic structure, temporal trends, and emerging frontiers in forensic dermatoglyphics research.

In this study, Total Link Strength (TLS) was used as a core indicator to quantify the cumulative strength of connections from a given node (e.g., a country, institution, or keyword) to all other nodes in a co-occurrence network, serving as a key measure of scientific connectivity. To comprehensively assess the scholarly impact and productivity of researchers, three bibliometric indices were incorporated: the h-index, g-index, and m-index. (1) h-index: It indicates that a researcher or journal has published h papers, each cited at least h times. It reflects both productivity and citation impact. For instance, a scholar with 10 publications, each cited ≥ 10 times, would have an h-index of 10. (2) g-index: As an extension of the h-index, the g-index places greater weight on highly cited publications. A researcher’s g-index is g if their top g articles have collectively received at least g^2 citations. (3) m-index: It normalizes the h-index by the academic age (*i.e.*, number of years since the researcher’s first publication), calculated as $m = h/n$. It reflects average scholarly influence over time, providing insights into research efficiency and sustainability.

For descriptive purposes, the study period was divided into two stages (1976–2006 and 2007–2025) based on visual examination of annual publication trends. The year 2007 was selected as an approximate boundary marking the observed increase in publication output, rather than a statistically determined change point. No formal change-point analysis was performed.

In addition, this study evaluated the Total Citation (TC) for countries, institutions, publishing journals, and individual authors. Each time a publication is cited—whether through self-citation or by others—the TC increases by one, cumulatively reflecting the overall citation volume of the work. To further evaluate the academic influence of publications, three derivative metrics were calculated:

1. Total Citations per Article (TC per Art): It is calculated by dividing the total number of citations received by a country, institution, or specific year by the total number of publications associated with that entity. It reflects the average scholarly impact per article. Formula:

$$\text{TC per Art} = \frac{\text{Total Citations}}{\text{Number of Publications}} \quad (1)$$

2. Total Citations per Year (TC per Year): It is calculated by dividing the total citation count of an article by the number of citable years, defined as the difference between the current year (2025) and the year of publication. For instance, a paper published in 2018 has a citable span of seven years. Formula:

$$\text{TC per Year} = \frac{\text{Total Citations}}{\text{Citable Years}} \quad (2)$$

3. Mean Annual Total Citations per Article (Mean TC per Year): To account for the effect of publication time on citation counts, it is calculated by dividing the TC per Art by the number of citable years. It provides a normalized measure of annual impact. Formula:

$$\text{Mean TC per Year} = \frac{\text{TC per Art}}{\text{Citable Years}} \quad (3)$$

3. Results

3.1. The Annual Trends in the Growth of Publications

Analyzing annual publication volumes and their temporal trajectories provides a clear lens for understanding a discipline's developmental dynamics and latent growth potential (Figure 3, Table S2). Since the inaugural publication on dermatoglyphics in forensic science in 1976, two broad research phases were identified based on visual examination of annual publication trends: (1) The Nascent Phase (1976–2006): Spanning nearly three decades, this initial period was marked by limited scholarly output, yielding a total of just 34 articles at an average rate of 1.10 publications per year. (2) The Rapid Expansion Phase (2007–2025): The subsequent period witnessed exponential growth, accumulating 762 articles at a markedly higher average annual rate of 40.1. Notably, the year 2025 alone contributed 136 publications, underscoring the acceleration of scholarly activity and the field's expanding trajectory.

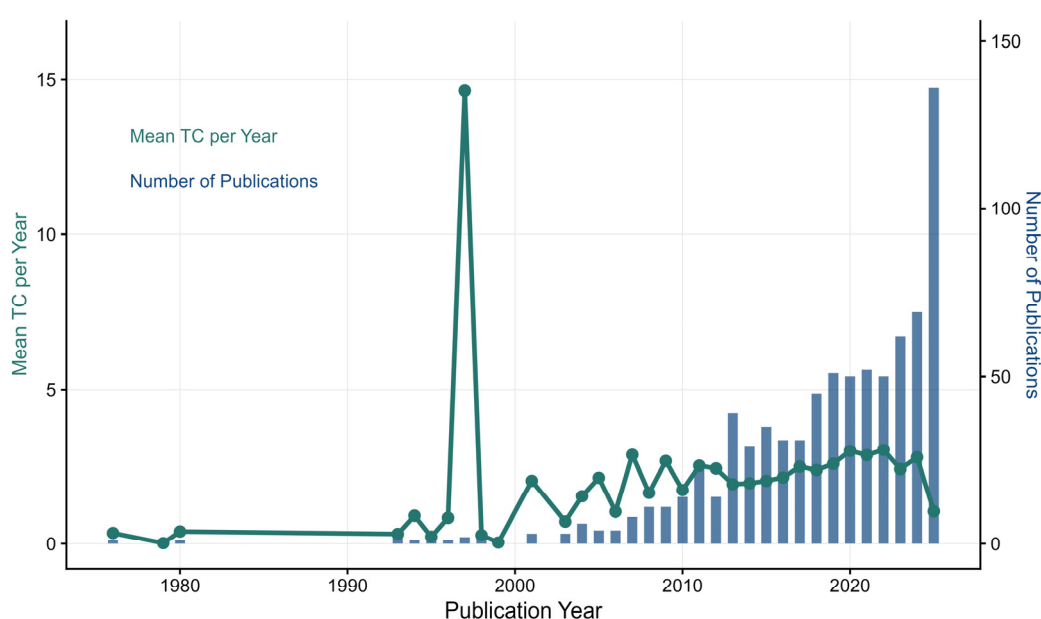
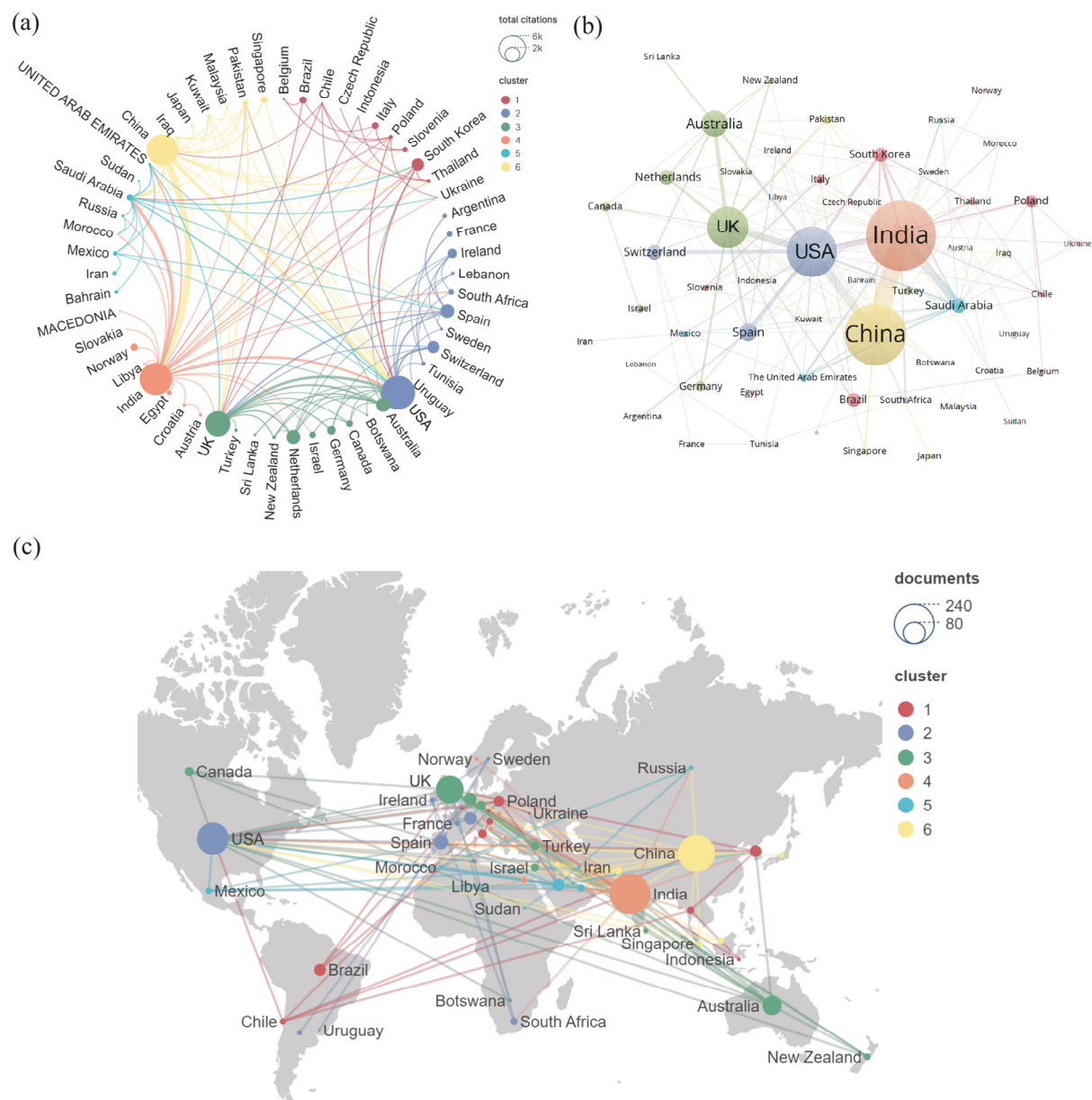


Figure 3. Number of publications and mean annual total citations per year (Mean TC per year), 1976–2025.

The annual mean citation rate surged to a pronounced peak of 14.65 in 1997 (Figure 3). Apart from this isolated peak, however, publications from the 20th century exhibited remarkably low publication and citation counts. In stark contrast, as the field entered the 21st century, citation activity has stabilized, maintaining a consistent mean of 2.2 citations per year. This sustained equilibrium indicates the field's enduring academic relevance and practical significance in contemporary forensic science.

3.2. Leading Countries

The 796 publications included in this study originated from 56 countries. India and China dominated in publication output, followed by the United States and the United Kingdom. Citation analysis further showed that these countries also accumulated the largest total citation counts, reflecting their dominant influence within the global research landscape of forensic dermatoglyphics (Table S3; Figure 4a). In contrast, the United States, the Netherlands, Germany, and the United Kingdom exhibited substantially higher citations per publication, indicating stronger academic impact despite comparatively lower productivity (Table S3).



International collaboration analysis based on TLS values, co-occurrence networks, and geographic collaboration mapping (Figure 4b,c) identified India, China, the United States, and the United Kingdom as the principal hubs of global cooperation in forensic dermatoglyphics research. SCP/MCP analysis further demonstrated that India and China relied predominantly on domestic publications, whereas the United States and the United Kingdom showed relatively stronger international collaboration patterns (Figure 5).

and optimization of novel fluorescent nanomaterials for latent fingerprint visualization, leading to rapid growth in publication output but relatively limited international influence. By contrast, studies from Western countries more frequently emphasized foundational forensic theory, statistical interpretation, algorithm development, and automated identification systems, which tended to achieve higher citation impact.

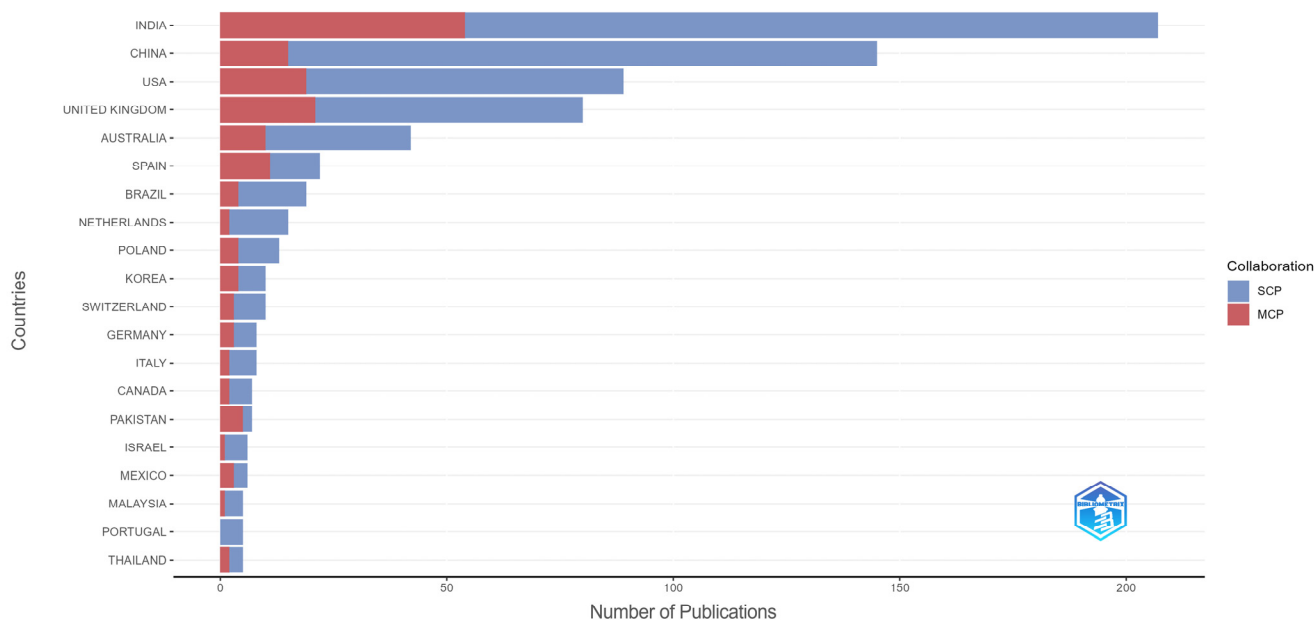


Figure 5. Intra- and inter-collaboration of various countries. SCP = Single Country Publication; MCP = Multiple Country Publication.

3.3. Institution Analysis

Among the 791 institutions analyzed, Tumkur University and Jain University in India ranked highest in publication output, whereas Sheffield Hallam University in the United Kingdom demonstrated the highest citations per publication (Table S4). Institutional co-authorship analysis identified five major collaboration clusters centered around Tumkur University, Panjab University, the Criminal Investigation Police University of China, the University of Lausanne, and Sheffield Hallam University (Figure 6).

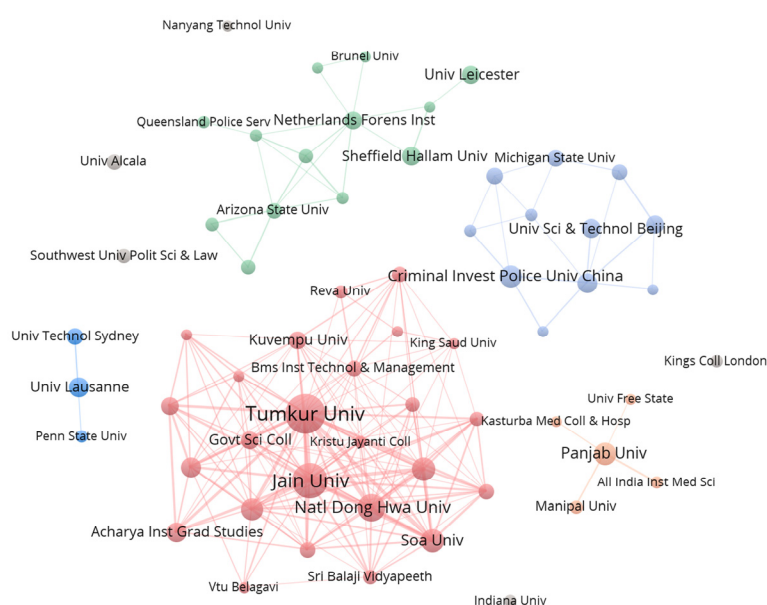


Figure 6. Institutional co-occurrence network map. Each node represents a research institution, with node size proportional to publication output. Edges denote collaborative relationships, and the spatial proximity of nodes reflects the closeness of

institutional partnerships. Nodes sharing the same color are clustered together, representing institutional communities with stronger collaborative ties.

Consistent with the country-level findings, institutions from developing countries contributed substantially to the growth of publications, particularly in studies on novel fingerprint visualization materials. However, institutions from Europe and North America exerted greater influence in high-impact research areas.

3.4. Sources of Publications

The leading publication venues are summarized in Table S5. Traditional forensic science journals, including *Forensic Science International*, *Journal of Forensic Sciences*, *Science & Justice*, and *Journal of Forensic and Legal Medicine*, constituted the principal outlets for forensic dermatoglyphics research, indicating a relatively stable disciplinary structure with established core journals. Meanwhile, high-impact engineering and computational journals such as *IEEE Transactions on Pattern Analysis and Machine Intelligence* achieved exceptionally high citation counts, reflecting the growing importance of biometric algorithms and intelligent identification technologies in this field.

Temporal publication trends further demonstrated that the *Journal of Forensic Sciences* and *Science & Justice* entered this field earlier, whereas *Forensic Science International* and the *Journal of Forensic and Legal Medicine* showed sustained expansion in later years (Figure 7).

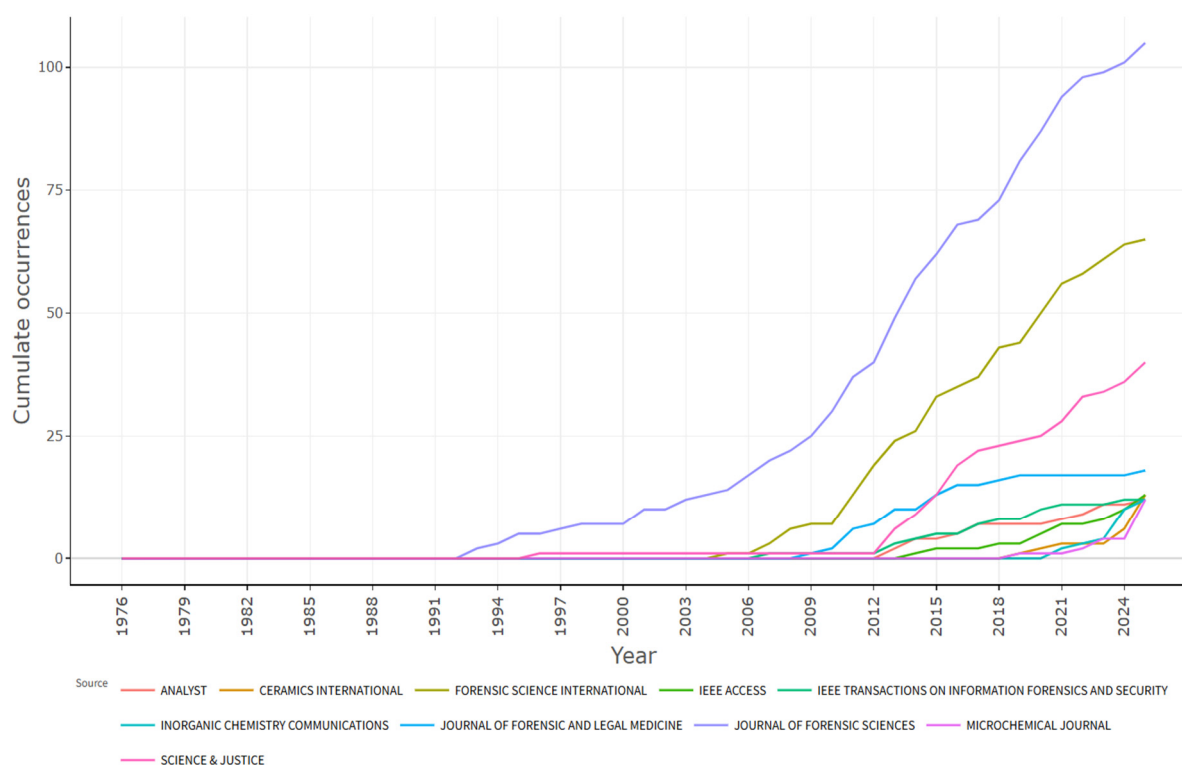


Figure 7. Annual publication trends of the top ten most productive journals in forensic dermatoglyphics research. The x-axis represents the year (1976–2025), and the y-axis indicates the annual publication count. Each colored curve corresponds to a journal.

3.5. Most Productive Authors

A total of 2392 authors contributed to the forensic dermatoglyphics literature. Authors with the highest h-index and g-index values included Nagabhushana Hanumanthappa, Sharma S. C., and Darshan Giriya Prabhukumar (Table 1). Author collaboration and citation network analyses confirmed their central positions within the collaborative landscape of the field (Figure 8a,b).

Table 1. Top 20 researchers ranked by h-index in forensic dermatoglyphics research.

Author	h-Index	g-Index	m-Index	NP	TC	PY-Start	TC per Year
Nagabhushana Hanumanthappa	26	36	2.60	69	1665	2017	208.13
Sharma S. C.	25	33	2.50	57	1301	2017	162.63
Darshan Giriypura Prabhukumar	23	30	2.30	30	976	2017	122.00
Basavaraj R. B.	18	19	1.80	19	669	2017	83.63
Premkumar H. B.	17	17	2.13	17	541	2019	90.17
Krushna B. R. Radha	16	24	3.20	37	643	2022	214.33
Prasad B. Daruka	14	14	1.56	14	560	2018	80.00
Manjunatha Krishtappa	13	18	3.25	27	371	2023	185.50
Wu Sheng Yun	13	18	3.25	27	371	2023	185.50
Francesca Simona	11	12	0.61	12	680	2009	42.50
Champod Christophe	10	11	0.48	11	316	2006	16.63
Jain Anil K.	10	10	0.50	10	810	2007	45.00
Kanchan Tanuj	10	15	0.59	16	248	2010	16.53
Lavanya D. R.	10	10	1.67	10	321	2021	80.25
Bradshaw Robert	9	10	0.50	10	618	2009	38.63
Krishan Kewal	9	15	0.45	17	227	2007	12.61
De Alcaraz-Fossoul Josep	8	12	0.57	12	157	2013	13.08
Gutierrez-Redomero Esperanza	8	11	0.50	11	196	2011	14.00
Zhang Meiqin	8	12	0.53	12	211	2012	16.23
Alonso-Rodriguez Concepcion	7	7	0.44	7	163	2011	11.64

Note: NP = Number of Publications; TC = Total Citations; PY-Start = Publication Years Start; TC per Year = Total Citation per Year.

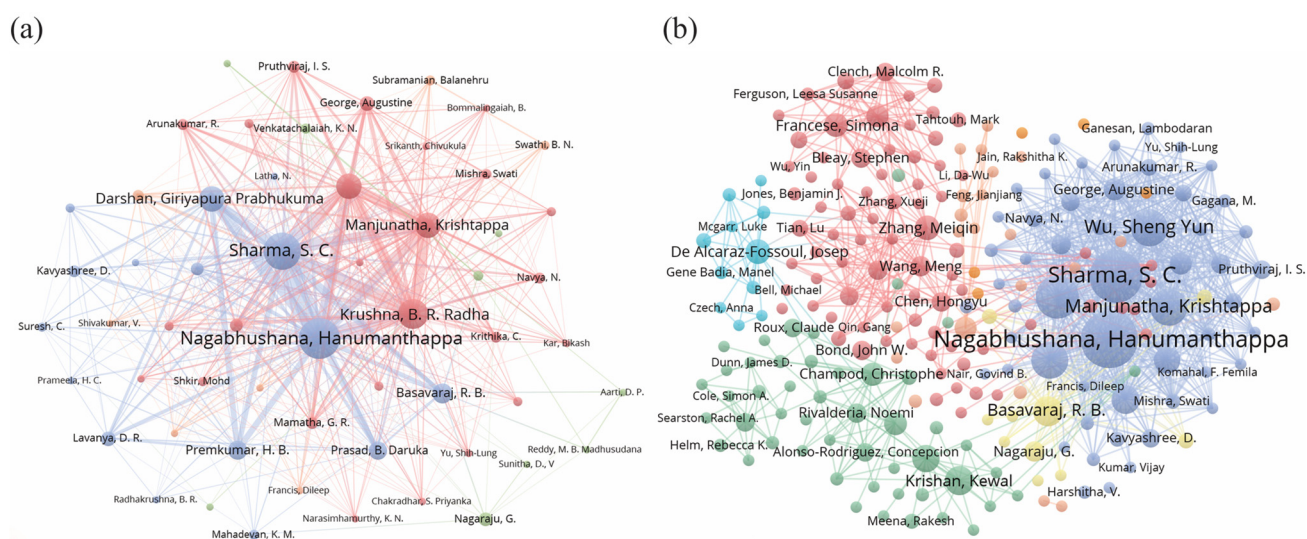


Figure 8. Author collaboration and citation networks in forensic dermatoglyphics research. **(a)** Author collaboration network. Each node represents an author, with node size proportional to publication output. Edges represent collaboration strength, and node colors denote research domains. **(b)** Author citation network. Each node represents an author, with node size proportional to publication output. Edge number and thickness indicate the extent of mutual citations, with thicker edges reflecting stronger citation links and closer collaboration. Colors indicate different clusters.

In contrast, the m-index highlighted several recently active scholars, including Manjunatha Krishtappa, Wu Sheng Yun, and Krushna B. R. Radha, who achieved rapid academic influence within a relatively short period. Publication timeline analysis further indicated that highly cited contributions from leading authors increased markedly after 2017 (Figure 9; Table S6).

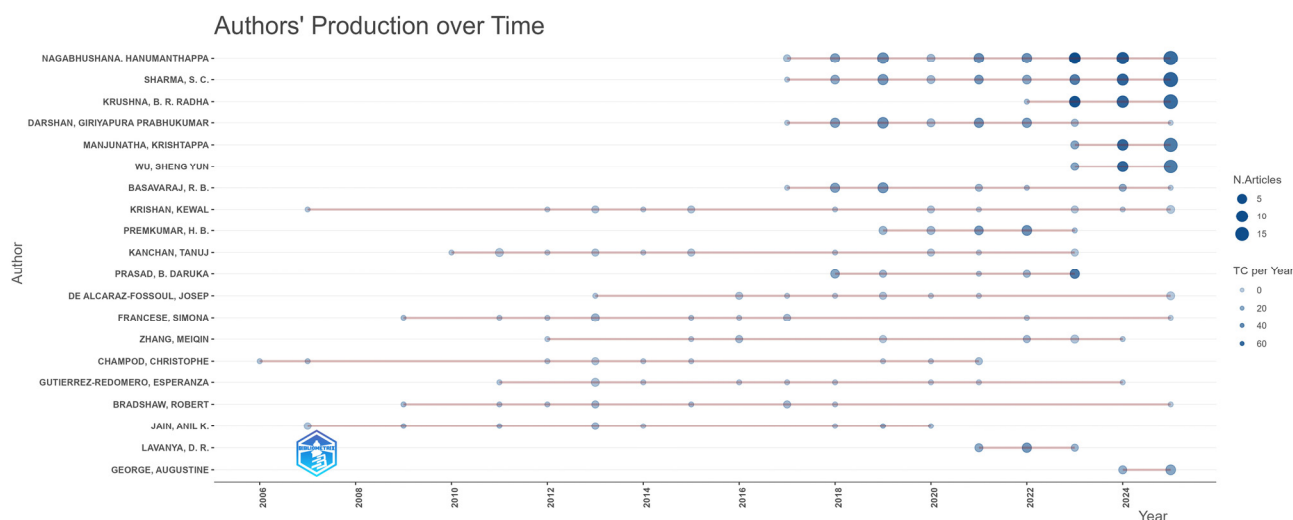


Figure 9. Publication-citation profiles of the top 20 researchers in forensic dermatoglyphics research. Red polylines depict temporal trends. Circle markers are scaled by the number of publications (N. Articles) and colored by TC per year (light-to-dark gradient).

3.6. Top 20 Most Cited Publications

The citation frequency of journal articles serves as a key indicator for assessing the academic impact of research outputs, with highly cited publications typically reflecting studies that have garnered substantial attention and recognition within the field. Based on citation frequency rankings, this study identified the 20 most-cited articles (Table 2). Among them, Jain A et al., 1997, *IEEE Transactions on Pattern Analysis and Machine Intelligence* ranked first with 850 total citations and an average of 30.36 citations per year [31]. This was followed by Edelman GJ et al., 2012, *Forensic Science International* (222 total citations; 17.08 citations per year) [32] and Jain AK et al., 2009, *IEEE Transactions on Pattern Analysis and Machine Intelligence* (209 total citations; 13.06 citations per year) [33].

Table 2. Top 20 most-cited publications in forensic dermatoglyphics research.

Article	TCCitable	Years	TC per Year	DOI
JAIN A, 1997, <i>IEEE T PATTERN ANAL</i>	850	28	30.36	10.1109/34.587996
EDELMAN GJ, 2012, <i>FORENSIC SCI INT</i>	222	13	17.08	10.1016/j.forsciint.2012.09.012
JAIN A, 2009, <i>IEEE T PATTERN ANAL</i>	209	16	13.06	10.1109/TPAMI.2008.242
JAIN A, 2011, <i>IEEE T PATTERN ANAL</i>	160	14	11.43	10.1109/TPAMI.2010.59
MNOOKIN JL, 2011, <i>UCLA LAW REV</i>	157	14	11.21	-
SOUSEDIK C, 2014, <i>IET BIOMETRICS</i>	155	11	14.09	10.1049/iet-bmt.2013.0020
WOLSTENHOLME R, 2009, <i>RAPID COMMUN MASS SP</i>	146	16	9.13	10.1002/rcm.4218
WANG M, 2015, <i>LANGMUIR</i>	134	10	13.40	10.1021/acs.langmuir.5b01151
TANG HW, 2010, <i>ANAL CHEM</i>	133	15	8.87	10.1021/ac9026077
CAO K, 2019, <i>IEEE T PATTERN ANAL</i>	122	6	20.33	10.1109/TPAMI.2018.2818162
CRANE NJ, 2007, <i>J FORENSIC SCI</i>	116	18	6.44	10.1111/j.1556-4029.2006.00330.x
DAI JF, 2011, <i>IEEE T PATTERN ANAL</i>	113	14	8.07	10.1109/TPAMI.2010.164
ZOU R, 2022, <i>ACS APPL MATER INTER</i>	110	3	36.67	10.1021/acsami.2c02563
FRANCESE S, 2013, <i>ANALYST</i>	98	12	8.17	10.1039/c3an36896c
NEUMANN C, 2007, <i>J FORENSIC SCI</i>	94	18	5.22	10.1111/j.1556-4029.2006.00327.x
WILLIAMS G, 2001, <i>J FORENSIC SCI</i>	92	24	3.83	-
MATKOWSKI WM, 2020, <i>IEEE T INF FOREN SEC</i>	86	5	17.20	10.1109/TIFS.2019.2945183
ZHOU ZP, 2017, <i>ANAL CHEM</i>	80	8	10.00	10.1021/acs.analchem.6b04498
MOUNTFORT KA, 2007, <i>ANAL CHEM</i>	80	18	4.44	10.1021/ac0623944
PAULINO AA, 2013, <i>IEEE T INF FOREN SEC</i>	80	12	6.67	10.1109/TIFS.2012.2223678

Note: TC = Total Citations; TC per Year = Total Citations per Year; -, no data.

Notably, several recent publications have demonstrated remarkable citation impact despite having fewer citable years. For instance, Zou R et al., 2022, *ACS Applied Materials & Interfaces* (36.67 citations per year) [34] and Cao K et al., 2019, *IEEE Transactions on Pattern Analysis and Machine Intelligence* (20.33 citations per year) [35] have achieved exceptionally high annual citation rates, underscoring their significant contribution to the field and the timely application of emerging technologies.

3.7. Author Keywords Analysis

Table S7 lists the top 20 most frequently occurring author keywords across 796 publications. Excluding the search terms “forensic science” and “fingerprint”, the keyword “latent fingerprint” was the most prevalent, appearing 212 times, followed by “photoluminescence” (67 occurrences) and “fingermark” (49 occurrences).

A keyword co-occurrence network was generated using CiteSpace (version 6.3.1) (Figure 10a), revealing three primary thematic clusters. Cluster 1 (red; $n = 64$) encompassed terms such as “forensic science”, “fingerprint”, and “identification”, indicating the central role of dermatoglyphics in forensic applications. Cluster 2 (orange; $n = 45$) included keywords such as “latent fingerprint” and “photoluminescence”, representing methodological advances in latent fingerprint detection. Cluster 3 (green; $n = 25$) comprised terms such as “biometrics”, “minutiae”, and “deep learning”, highlighting emerging computational approaches to dermatoglyphics analysis.

The temporal evolution of keywords (Figure 10b) and citation bursts analysis (Figure 10c) reveal distinct stage-wise transitions in the field’s research focus. Earlier publications concentrated primarily on foundational concepts within Clusters 1 (red), such as “fingerprint” and “identification”. In contrast, recent studies have increasingly shifted toward technically sophisticated and application-oriented terms in Clusters 2 (orange) and 3 (green), including “latent fingerprint”, “photoluminescence”, and “feature extraction”.

3.8. Three-Field Plot Analysis Representing Countries-Sources-Authors Keywords

The three-field plot of countries, sources, and author keywords (Figure 11) provides a visually intuitive representation of knowledge flows and the interconnections among nations, journals, and research themes. Regarding country–journal associations, research outputs from developed countries such as the United States and the United Kingdom are predominantly featured in leading forensic journals, including the *Journal of Forensic Sciences* and *Forensic Science International*. In contrast, publications from developing countries such as India, China, and South Korea are more frequently found in journals focused on technical innovation, such as *Inorganic Chemistry Communications* and *Science & Justice*. This divergence may reflect both the distinct research orientations of these countries and the thematic focus of the respective journals.

With respect to journal–keyword relationships, forensic science journals—exemplified by *Forensic Science International* and the *Journal of Forensic Sciences*—are primarily associated with foundational terms such as “fingerprint” and “forensic science”, underscoring their central role in advancing fingerprint-related research within the forensic domain. Meanwhile, chemistry-oriented journals like *Inorganic Chemistry Communication* and computer science-oriented journals such as *IEEE Transactions on Pattern Analysis and Machine Intelligence* are more closely linked to technical keywords including “photoluminescence” and “biometrics”, reflecting a technology-driven research agenda focused on dermatoglyphics image acquisition and recognition.

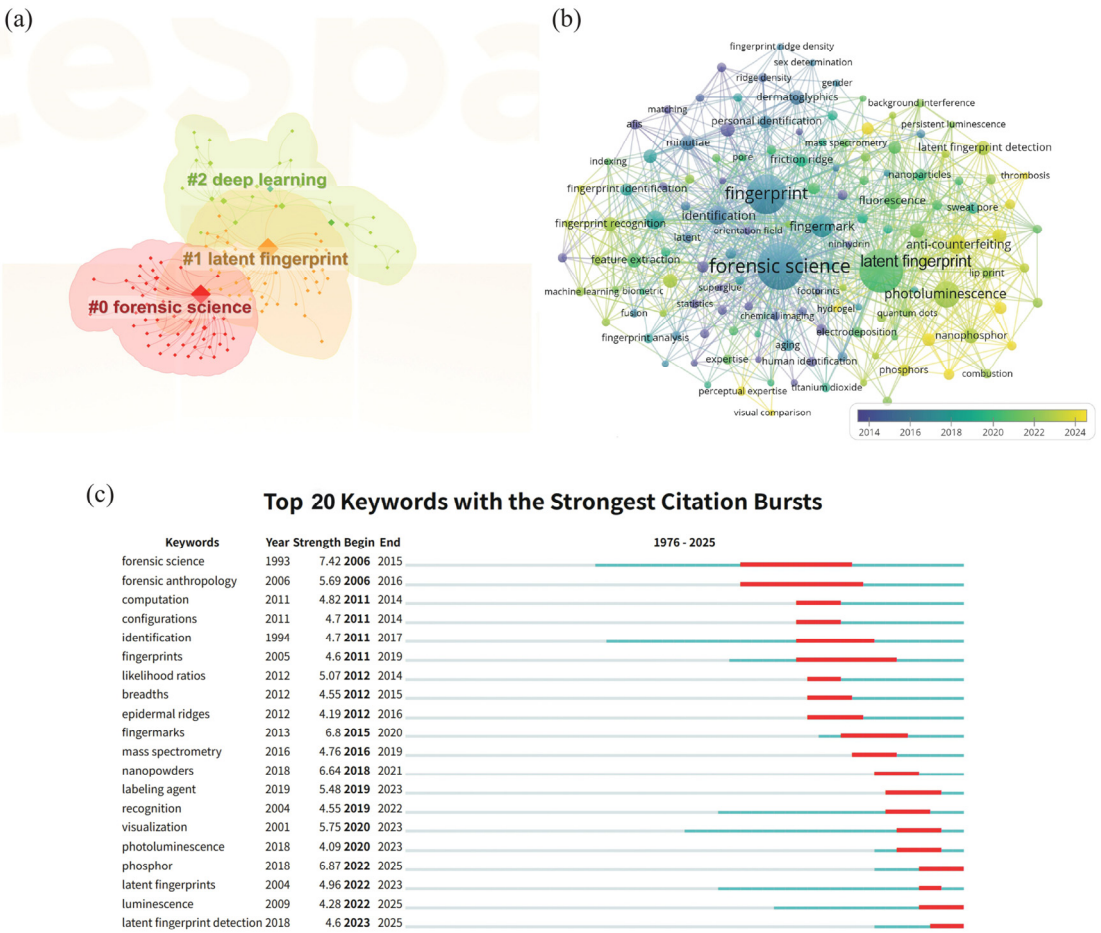


Figure 10. Author keywords visualization maps. **(a)** Keyword clustering map generated by CiteSpace: nodes represent keywords, links indicate co-occurrence relationships between keywords, and different colors denote distinct clusters. **(b)** Temporal evolution visualization: this map displays keywords based on their average appearance time, with green and blue nodes indicating keywords predominantly used in earlier publications, and yellow nodes representing more recent research trends. **(c)** Citation Burst Analysis: the horizontal axis represents time, with each line corresponding to a keyword; red bars denote periods of citation bursts, indicating a sudden increase in scholarly attention, while blue bars reflect sustained citation periods.

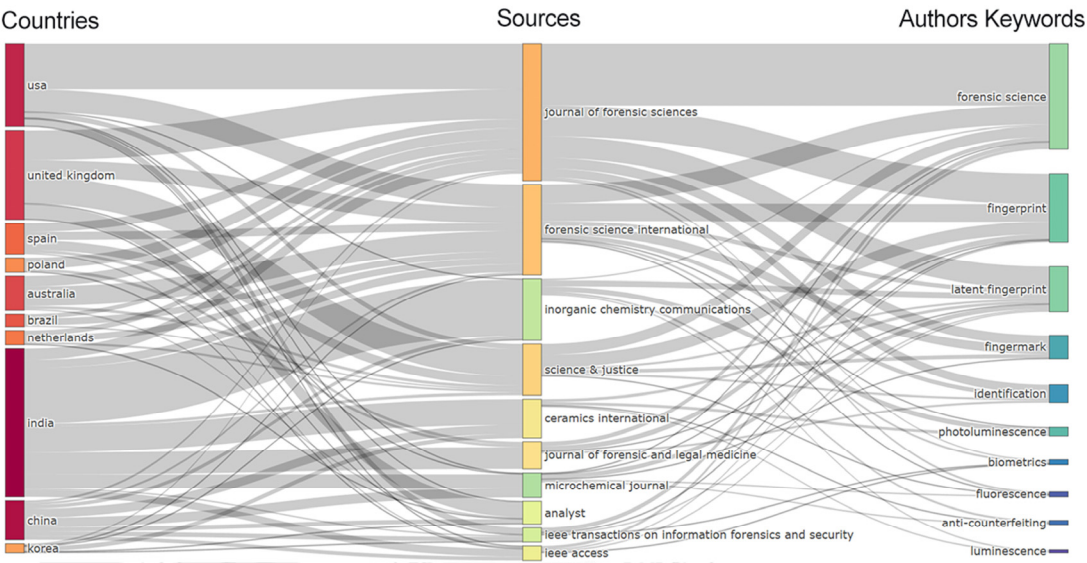


Figure 11. Three-field plot analysis of Countries–Sources–Author Keywords. The tripartite visualization displays Countries (left), Sources (middle), and Author Keywords (right). Box heights correspond to publication volume, while connection widths indicate association strengths across domains.

4. Discussion

4.1. Publication and Citation Analysis

This study presents a comprehensive bibliometric analysis of 796 forensic dermatoglyphics publications retrieved from the WoS Core Collection. The earliest traceable work dates to 1976, when the feasibility of fingerprint representation, recognition, and classification for forensic applications was first validated [36]. Owing to the inherent advantages of fingerprints as biometric evidence for individual identification, they have long been used in crime scene investigations. However, early practices primarily relied on ink-based palm and finger impressions or on-site visual examination, both of which were inefficient and low-quality. Not until the early 1980s, with the widespread adoption of personal computers and the emergence of optical scanning technologies, did researchers begin focusing on advanced palm and fingerprint image acquisition and processing techniques [14]. Early efforts during this period focused on the design and application of fingerprint verification systems [37,38]. In 1997, Professor A. Jain and his team developed a two-stage automated fingerprint verification system that integrated improved minutiae extraction and elastic matching algorithms to enable rapid, accurate online verification [31]. This seminal work remains the most cited publication in the field.

Entering the 21st century, with the global expansion of AFIS, research in forensic dermatoglyphics has grown steadily. Driven by breakthroughs in imaging technology and functional materials, innovations in integrated intelligent sensing-computing architectures, and the rising demand for latent fingerprint analysis in forensic practice [39–41], the field has witnessed accelerating technological iteration and growing interdisciplinary integration. Consequently, the annual number of publications has continued to increase, spurring a new wave of research interest. This pronounced growth trend underscores not only the academic value of forensic dermatoglyphics but also its evolving innovative potential driven by modern technology, highlighting the alignment of research hotspots with technological advancement.

4.2. Countries, Institutions, and Authors Analysis

Bibliometric analysis reveals a clear dichotomy in the global landscape of forensic dermatoglyphics research. India and China, along with their affiliated institutions, dominate in publication volume. However, academic impact, as measured by citations per publication, remains higher in developed countries such as the United States, New Zealand, Germany, and the United Kingdom. Despite leading in total output, India and China rank only 10th and 8th in citations per publication, respectively.

At first glance, this disparity may appear to reflect a later start in forensic research in these countries. However, a closer examination suggests deeper differences in research focus and dissemination patterns. Western scholars have largely concentrated on foundational areas. These include chemical analysis of fingerprint residues [32,42], evidence interpretation [43], associations with human phenotypic traits [26,44], and algorithm development [31,33]. Influential researchers, such as Professor Anil K. Jain at Michigan State University, have established widely adopted frameworks in biometrics and pattern recognition. These early contributions serve as methodological cornerstones and have shaped industry standards, including the optimization of automated fingerprint identification systems. As a result, such work attracts citations from multiple disciplines, including computer science, law, and criminology, thereby achieving sustained and widespread academic influence.

In contrast, the rapid growth of publications from India and China is mainly driven by research on fluorescent nanomaterials for latent fingerprint visualization. Many studies focus on doping rare-earth ions, such as Eu^{3+} , Tb^{3+} , Sm^{3+} , Dy^{3+} , and Ho^{3+} , into various host matrices to develop luminescent powders [45–47]. Researchers such as Professor Nagabhushana Hanumanthappa have contributed to the advancement of optical materials for enhancing latent fingerprints. However, materials-oriented studies often produce a large number of incremental methodological variations with limited forensic validation. Consequently, their

influence is frequently confined to specialized materials science communities and rarely extends to broader forensic, judicial, or interdisciplinary applications.

More importantly, this imbalance suggests a broader structural issue within contemporary forensic dermatoglyphics research: advances in materials synthesis and optical performance may not be matched by equivalent progress in practical forensic applicability, interpretability, and evidential reliability. Although bibliometric indicators alone cannot establish operational readiness, this pattern highlights the need to make forensic validation central to any research claiming practical applicability. We therefore advocate a moratorium on publications claiming advances in the development of forensic dermatoglyphic marks based solely on optical optimization unless they include a standardized forensic validation module. Such a module should incorporate representative donors and substrates, controlled aging and environmental exposure, comparison with established development techniques, and blinded assessment using predefined criteria for ridge-detail quality, identification suitability, and reproducibility.

Accordingly, the discrepancy between publication quantity and academic influence should be viewed as a call to reassess research priorities. Future progress requires a transition from material-centered innovation toward problem-oriented forensic research, with performance under realistic investigative conditions as the principal measure of practical value. Priority forensic challenges should include developing latent friction ridge impressions on spent cartridge casings, recovering aged or degraded prints, and developing prints exposed to fire-related heat or water immersion. Additional priorities include reducing background interference on patterned or strongly fluorescent substrates and recovering ridge detail from contaminated surfaces.

4.3. Source Journals Analysis

Source journal analysis shows that *Forensic Science International*, *Journal of Forensic Sciences*, *Science & Justice*, and *Journal of Forensic and Legal Medicine* exhibit outstanding performance in both h-index and g-index, demonstrating their dual strengths in productivity and academic impact. As authoritative, comprehensive forensic science journals, these four publications cover a broad spectrum of topics, supporting the in-depth application of dermatoglyphics research in crime scene reconstruction and digital evidence correlation. This underscores the growing demand in contemporary forensic science for integrating multi-source evidence to support individual identification and case traceability.

Furthermore, journals in information technology and materials chemistry also play a significant role in dermatoglyphics research. For instance, *IEEE Transactions on Information Forensics and Security*, which focuses on information security and digital forensics, has increasingly become a key technological platform for advancing dermatoglyphics recognition algorithms and digital evidence extraction. Similarly, *Inorganic Chemistry Communications* focuses on developing novel luminescent and nanomaterials for latent fingerprint visualization. Collectively, this multidisciplinary convergence spanning information technology, materials science, forensic science, and judicial practice has substantially expanded the breadth and depth of dermatoglyphics applications in forensic contexts.

4.4. Key Focus Areas and Emerging Trends

Keyword co-occurrence analysis shows that forensic dermatoglyphics research primarily focuses on two core areas: (1) biometric feature extraction and recognition algorithms, and (2) the development of novel fluorescent nanomaterials for latent fingerprint visualization. Both of these areas constitute fundamental theoretical investigations into the acquisition of latent dermatoglyphics and individual forensic identification, with future academic and industrial hotspots expected to continue to deepen along these two dimensions.

The advancement of dermatoglyphics feature extraction and recognition technologies is closely linked to the evolution of image processing methods. Machine learning classifiers, such as support vector

machines (SVMs), have been applied to extracted dermatoglyphics features to support recognition tasks involving high-dimensional data [16]. Entering the 21st century, deep learning has achieved revolutionary breakthroughs; notably, the application of Convolutional Neural Networks (CNNs) has enabled precise matching between contactless and contact-based fingerprint images [17]. In recent years, research has increasingly focused on lightweight networks, attention mechanisms, and multimodal fusion to balance high accuracy with real-time performance and resource constraints. Deep learning and multimodal biometric fusion will likely continue to push performance boundaries in tasks such as feature extraction, image enhancement, and classification recognition, laying a solid foundation for the practical deployment of dermatoglyphics identification technologies.

Owing to the inherent complexity of forensic practice, dermatoglyphics marks left at crime scenes are often invisible to the naked eye and may be fragmentary; consequently, latent mark development has become a prerequisite and critical step in forensic workflows, with a distinct trend toward multidisciplinary integration. Recent studies have demonstrated that nanophosphors such as barium lanthanum zinc oxide (BLZO) nanoparticles and Eu^{3+} -doped strontium cerium oxide ($\text{SrCeO}_3:\text{Eu}^{3+}$ NPs) can yield high-contrast images at Level I–III details, with sensitivity nearly two orders of magnitude higher than conventional powder methods, providing novel approaches for detecting aged or low-residue fingerprints [48,49]. Concurrently, rare-earth-based photoluminescence (PL) techniques can effectively suppress background autofluorescence and improve signal-to-noise ratios due to their high quantum yield, long-lived fluorescence, and multiband tunability. These advantages have led to their increasing application in latent fingerprint enhancement and highlight their broad prospects for future evidence collection [50].

5. Bridging the Translational Gap: Judicial Admissibility and Analytical Compatibility

Building on two research areas identified through keyword co-occurrence analysis, we discuss judicial admissibility and validation challenges for recognition technologies, together with standardized evaluation and biological and analytical compatibility issues for novel visualization materials. Notably, this discussion presents a narrative interpretation informed by the literature rather than conclusions directly derived from the bibliometric analysis.

5.1. Judicial Admissibility and Validation Challenges of Dermatoglyphics Evidence: From Traditional Empirical Verification to Artificial Intelligence

For decades, fingerprint identification was widely regarded as a virtually infallible forensic technique, with experts often presenting categorical conclusions of certainty. However, the 2004 Madrid train bombing investigation and the subsequent Mayfield misidentification case exposed the limitations of subjective interpretation and challenged the long-standing assumption of error-free fingerprint evidence [51]. Furthermore, a classic study by Dror et al. highlighted the profound impact of “contextual bias”, demonstrating that experienced examiners often reversed their own previously correct identifications when exposed to misleading contextual information related to the Mayfield case [52]. In response, the forensic science community conducted large-scale empirical validation studies to quantify examiner performance. A landmark study by the FBI and Noblis reported a false-positive rate of approximately 0.1% and a false-negative rate of 7.5% among fingerprint examiners, while also revealing substantial variability in decision-making [53]. Together with findings from proficiency-testing programs, these results dismantled the “zero-error” paradigm and accelerated the transition of forensic identification toward probabilistic evaluation frameworks and rigorous blind verification procedures, similar to those adopted in forensic DNA analysis.

The transformation of fingerprint examination from claims of absolute certainty to empirically quantified error rates provides an important lesson for the judicial adoption of artificial intelligence (AI)-based dermatoglyphics analysis. Although AI significantly enhances the efficiency of dermatoglyphics

feature extraction and matching, its admissibility in judicial practice remains a formidable challenge. Under the Daubert standard, scientific evidence must be adequately valid and reliable, which necessitates evaluating methodological validation, known error rates, and compliance with established standards [54,55]. Many contemporary AI systems operate as “black-box” models, whose internal decision-making processes remain difficult to interpret and to independently validate [43]. This opacity, compounded by algorithmic bias, uncertain error rates, and probabilistic outputs, significantly weakens the scientific persuasiveness of AI-generated conclusions. In addition, unlike DNA profiling, which relies on explicit allele-matching criteria established through robust genetic markers such as STRs and SNPs [56,57], dermatoglyphics identification still lacks universally accepted standards regarding the required number and quality of corresponding minutiae. To improve the scientific credibility and legal admissibility of AI-assisted fingerprint evidence, future research should prioritize more transparent and interpretable “glass box” AI frameworks, rigorous validation under case-representative conditions, standardized reporting of algorithmic performance and error rates, and independent peer-reviewed evaluation [58–60]. To operationalize these principles, we propose that the forensic community develop adversarial blind proficiency tests for AI systems. These tests would extend the empirical performance assessment exemplified by the FBI/Noblis study and incorporate safeguards against contextual influence highlighted by Dror et al. Specifically, these tests should combine representative casework samples with deliberately challenging impressions targeting documented or suspected algorithmic weaknesses, including severe distortion, partial ridge detail, low contrast, and visually similar non-matching prints. Prints from siblings could be included as an exploratory challenge subset, without presuming that biological relatedness itself constitutes an established algorithmic failure mode. Independent laboratories should administer these tests using verified ground truth and datasets excluded from model training and tuning, with ground-truth labels and potentially biasing case information withheld from operators and examiners. Model versions and decision thresholds should be fixed before testing, and AI-only performance should be assessed separately from examiner performance with AI assistance. Prespecified reporting should include false-positive and false-negative rates with confidence intervals, inconclusive or abstention rates, and performance stratified by impression quality and challenge type. Results from representative samples and deliberately adversarial subsets should be reported separately to avoid treating stress-test error rates as estimates of routine casework performance. Such testing would provide a concrete evidential basis for Daubert hearings on the admissibility of scientific evidence by documenting the evaluated system’s performance, failure conditions, and limits of applicability, while not implying that successful testing alone guarantees admissibility. Furthermore, AI should function as a decision-support tool rather than an autonomous decision-maker, with human examiners remaining responsible for contextual interpretation and judicial explanation of the results.

5.2. Lack of Standardized Evaluation Systems for Novel Fingerprint Reagents

Despite the rapid emergence of fluorescent nanomaterials for latent fingerprint visualization, the forensic community still lacks unified technical standards for evaluating these materials. Most current studies focus primarily on fluorescence intensity, sensitivity, and image contrast, whereas considerably less attention has been paid to operational reproducibility, substrate adaptability, environmental stability, and biosafety. Consequently, many newly developed materials demonstrate promising laboratory performance but remain insufficiently validated for routine forensic applications. Future research should therefore shift from the isolated pursuit of higher luminescence efficiency toward the establishment of standardized operational protocols and comprehensive evaluation systems. Before incorporation into routine forensic workflows, novel reagents should undergo systematic assessments covering sensitivity, contrast quality, stability across complex substrates, operator-dependent variability, inter-operator variability, long-term storage stability, and potential risks to human health and the environment. Specifically, evaluation should require multiple technicians to apply the reagent independently under a common protocol, including

technicians outside the developing laboratory. Performance metrics should quantify inter-operator variability in development success rates, image contrast, and ridge-detail quality, rather than relying solely on results obtained under conditions optimized by the reagent developers. The establishment of internationally recognized technical standards will be essential for improving reproducibility, inter-laboratory comparability, and judicial credibility.

5.3. *Biological Compatibility and Downstream Molecular Interference*

While latent prints are inherently invisible at crime scenes, the application of highly sensitive luminescent materials significantly lowers their detection limits. However, because latent print residues naturally harbor trace cellular DNA alongside various chemical substances (e.g., drugs, metabolites, and environmental pollutants), forensic investigations frequently require the joint analysis of the print and these co-existing targets. This introduces a critical challenge regarding the compatibility of development reagents with subsequent multiplex analyses. Research indicates that certain fluorescent materials can adversely affect downstream procedures by directly damaging DNA strands, reducing extraction yields, inhibiting PCR amplification, or interfering with capillary electrophoresis signals [61,62]. Furthermore, these materials may alter the chemical structures of endogenous components and disrupt subsequent mass spectrometry detection, thereby severely undermining the reliability of secondary analyses [63]. These concerns highlight the need to incorporate biological compatibility and analytical non-interference as fundamental prerequisites in the development of next-generation latent print visualization materials. In particular, fluorescent nanomaterials, including rare-earth-ion-doped powders and other highly reactive luminescent probes, should undergo rigorous mechanistic validation prior to forensic application. Such evaluations should determine whether these materials induce DNA fragmentation, exhibit non-specific binding to target nucleic acids, suppress amplification efficiency, or alter the detectability of trace biomolecules during downstream omics analyses. Accordingly, future research should prioritize developing biologically inert visualization reagents that preserve endogenous molecular information while maintaining high-quality extraction of ridge detail. Establishing an integrated evaluation framework spanning fingerprint development, molecular extraction, and downstream analytical workflows will be essential for enabling simultaneous dermatoglyphics and molecular genetic identification from the same forensic trace.

6. Study Limitations and Future Directions

Several limitations inherent to this bibliometric analysis should be acknowledged, and its findings interpreted in the context of the methodology employed.

First, a potential English-language bias exists. Although China and India are major contributors to this field, our methodology may systematically exclude substantial practice-oriented research published in local languages—particularly studies in Chinese core journals that document frontline policing and forensic identification. Consequently, while this analysis captures the knowledge structure of the global English-speaking academic community, it may underestimate the actual regional penetration and practical implementation of these techniques.

Second, our exclusive reliance on the WoS Core Collection introduces a database selection bias. WoS favors high-impact, internationally oriented journals, thereby overrepresenting fundamental and methodology-driven research, such as algorithm development (e.g., IEEE journals) or material innovations (e.g., ACS journals). Conversely, practice-oriented studies detailing forensic practice fingerprint recovery, operational workflows, or case-based applications are often indexed more comprehensively in databases like Scopus or PubMed. Thus, our results primarily reflect the “international academic frontier” rather than the full diversity of frontline forensic practice.

Third, confining searches to title, abstract, and keyword fields may have inadvertently excluded pertinent articles. Although our search explicitly included “palmprint”, “footprint”, and “dermatoglyphic*” alongside fingerprint-related terms, keyword-based retrieval may nevertheless have missed relevant palmprint and footprint studies that employed alternative or specialized terminology. Requiring “forensic*” in the Topic field may also have excluded studies whose forensic applications were discussed only in the full text. This highlights the trade-off between search specificity and sensitivity, and the potential underrepresentation of relevant research that lacks explicit forensic terminology in the searched fields. Additionally, the visualization and analytical tools employed (*i.e.*, VOSviewer, CiteSpace, and SCImago Graphica) may introduce methodological constraints due to differences in algorithms, parameter settings, and data processing strategies, which could affect network structures and clustering results.

Future studies should aim to mitigate these limitations by integrating multiple databases (including WoS, Scopus, and PubMed) to enhance coverage and reduce language bias, expanding search strategies beyond core fields to improve retrieval sensitivity, and combining multiple bibliometric tools with cross-validation across platforms to strengthen the robustness and reproducibility of findings.

7. Conclusions

This bibliometric analysis demonstrates that forensic dermatoglyphics has evolved into a highly interdisciplinary field driven primarily by advances in artificial intelligence and fluorescent visualization materials. However, the current research landscape also reveals a critical structural limitation. Materials scientists frequently prioritize the synthesis and optical optimization of novel luminescent reagents, whereas computational researchers largely focus on algorithmic performance using standardized datasets. In contrast, practical forensic investigations involve highly complex conditions, including degraded, overlapping, contaminated, and substrate-dependent latent prints. This disconnect between laboratory-oriented innovation and operational forensic demands represents one of the major challenges restricting translational progress in the field. Future breakthroughs will therefore depend not only on technological advancement itself, but also on the deep integration of materials science, artificial intelligence, analytical chemistry, and forensic practice. Equally important is the establishment of standardized evaluation systems addressing reproducibility, biological compatibility, algorithmic interpretability, and judicial admissibility. Such efforts will be essential for transforming emerging technologies from experimental concepts into reliable forensic tools applicable to real-world criminal investigations and judicial proceedings.

Supplementary Materials

The following supporting information can be found at: <https://www.sciepublish.com/article/pii/1254>, Table S1: Information of 796 articles of Dermatoglyphics in Forensic Science: A Bibliometric Analysis from 1976 to 2025; Table S2: Annual publication output and citation impact, 1976–2025; Table S3: Top 20 countries in forensic dermatoglyphics research ranked by number of publications; Table S4: Top 20 institutions in forensic dermatoglyphics research ranked by number of publications; Table S5: Top 20 journals in forensic dermatoglyphics research ranked by h-index; Table S6: Contribution of the top 20 authors over different years; Table S7: Top 20 most frequently occurring author keywords in forensic dermatoglyphics research.

Statement of the Use of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used ChatGPT in order to polish the language and create vector graphic elements for the graphical abstract. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Author Contributions

Z.H.: Conceptualization, Data Curation, Formal Analysis, Visualization, Writing—Original Draft Preparation; J.L.: Conceptualization, Data Curation, Formal Analysis, Visualization; J.C.: Data Curation; Q.Y.: Data Curation; Q.W.: Data Curation; S.L.: Data Curation; J.L.: Supervision; C.L.: Project Administration, Supervision; R.Z.: Project Administration, Supervision, Writing—Review & Editing; S.Z.: Project Administration, Supervision, Writing—Review & Editing.

Ethics Statement

Not applicable for studies not involving humans or animals.

Informed Consent Statement

Not applicable for studies not involving humans.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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