# **BEYOND HAIR LOSS: EXPLORING THE EVOLUTION OF ANDROGENETIC ALOPECIA RESEARCH BASED ON TEXT MINING AND BIBLIOMETRICS**

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Abstract: In this study, word dynamics, co-occurring phrases, and keyword frequency in the area of androgenetic alopecia were thoroughly analysed during a ten-year period. The study tracks changes in word usage, frequency, and context and identifies variations in the distribution and usage patterns of keywords, subjects, and co-occurring phrases using natural language processing techniques and graph theory-based approaches. The research reveals hidden linkages and patterns between diverse ideas, shedding light on the co-occurrence patterns of numerous phrases in the literature on androgenetic alopecia. The study emphasises the value of clearly visualising and disseminating findings to a large audience. In order to communicate the findings of the 10-year trend analysis to patrons, legislatures, and other pertinent audiences, data visualisation tools, infographics, and reports are used. This makes sure that the results are useful, effective, and easily accessible so that they can guide the creation of policies and decisions pertaining to androgenetic alopecia. The results of this study may have substantial ramifications for academics, medical professionals, policymakers, and other industry participants. The research can lead future research paths, prioritise research areas, and suggest areas that require additional examination by highlighting key research challenges and pointing out gaps in the study of androgenetic alopecia. Identifying emergent study issues, analysing the changing patterns in the area, and establishing research strategies can all benefit from an analysis of word dynamics and correlations among terms. The results reveal hidden relationships and patterns, advance knowledge of the research environment in this area, and influence androgenetic alopecia research objectives and policies.

Keywords: Hair loss; Androgenetic alopecia; Bibliometric; Text citation; Data visualizations

# **1 INTRODUCTION**

Male pattern baldness, also known as androgenetic alopecia, is a prevalent disorder marked by hair loss that follows a particular pattern, usually beginning at the hairline and crown of the scalp. Men and women are also affected, albeit men are more likely to experience it [1]. A hormone termed dihydrotestosterone (DHT), an androgen hormone, is thought to have a major role in the development of androgenic alopecia [2].

On the other side, bibliometrics is the quantitative examination of scholarly works, such as journals, articles, and citations, in order to identify patterns and trends in scientific inquiry. Bibliometrics can shed light on a researcher's publishing output, influence, and patterns of collaboration in addition to the development of their study topics over time [3]. In order to comprehend the research landscape, identify relevant research areas, and monitor research trends, there has been an increase in interest in studying androgenic alopecia in recent years [1]. Such an analysis can point out regions of high effect, identify research gaps, and suggest future research initiatives in the area of androgenic alopecia.

Text mining in bibliometrics involves the automated extraction and analysis of data from text-based sources, such as scholarly articles, to uncover patterns and trends. Recent studies have utilized text mining techniques to analyze research on alopecia, a common hair loss condition, to identify research trends, influential publications, and research gaps, providing valuable insights for further research and clinical practice [4].

Using bibliometrics and trend analysis, this report seeks to give a broad picture of the state of androgenic alopecia research today [5]. The tries to review the body of knowledge on androgenic alopecia, emphasise important areas for future research, and go over the methods and conclusions of current bibliometric studies [6]. Using bibliometric techniques also highlight new trends and research gaps in the area and offer suggestions for further investigations. This work intends to contribute to a better understanding of the research landscape in this area and offer insights for academics, clinicians involved in androgenic alopecia research and management by analysing the bibliometric trends in research on androgenic alopecia [3, 7].

# **2 LITERATURE REVIEW**

A useful tool for evaluating research trends and determining key publications in a certain topic is bibliometric analysis. Numerous studies have examined the scientific literature and the state of the research landscape using bibliometric methodologies.

Bai et al. performed a bibliometric analysis on research related to myocardial ischemia/reperfusion injury from 2012 to 2021[8]. They employed bibliometric techniques, including keyword co-occurrence and citation analysis, to identify

research trends and influential publications in this field. Their results highlighted the most productive countries, institutions, and journals, as well as key research topics and research trends, providing insights into the research landscape of myocardial ischemia/reperfusion injury.

Du and Hou conducted a hotspots analysis and provided perspectives on Prussian Blue Analogues (PBAs) in the field of environment and energy research [9]. They utilized the CiteSpace tool to identify research hotspots, key authors, and research trends in the field of PBAs. Their findings revealed the emerging research areas, influential publications, and research collaborations related to PBAs, providing insights into the current research landscape and potential future research directions.

Lei et al. conducted a bibliometric analysis of the top 50 most influential articles on external ventricular drains, as published in the World Neurosurgery journal [10]. External ventricular drains are widely used in neurosurgical practice to manage intracranial pressure in patients with various neurologic conditions. Lei et al. identified and analyzed these top 50 articles based on citation counts, publication years, authors, countries, and journals. The authors found that these influential articles were published between 1951 and 2019, with the majority of them published in the past two decades. The United States and Canada were the most productive countries in terms of published articles, and the most prolific authors and institutions were also identified. Furthermore, the study revealed the journals that published the most influential articles, highlighting the significance of specific journals in the field of neurosurgery.

This bibliometric analysis by Lei et al. provides valuable insights into the historical and geographical trends in the literature on external ventricular drains. By identifying the most influential articles, authors, institutions, and journals, this study sheds light on the key contributors and publications that have shaped the field of neurosurgery in this particular area. The findings of this study may be useful for researchers, clinicians, and policymakers to understand the current state of the literature and to identify important research directions in the field of external ventricular drains.

In a different field of research, Nabgan et al. conducted a bibliometric analysis of the application of non-precious materials for the pyrolysis reaction of plastic waste, as published in the Arabian Journal of Chemistry[11]. Pyrolysis is a thermochemical process that can convert plastic waste into valuable products, such as fuels and chemicals, and non-precious materials are catalysts used in pyrolysis reactions. The authors analyzed the publications on this topic based on citation counts, publication years, authors, countries, and keywords. The study revealed the trends in research on non-precious materials for plastic waste pyrolysis, including the evolution of research interests over time, the most influential authors and institutions, and the most commonly used keywords in the literature.

This bibliometric analysis by Nabgan et al. provides a comprehensive overview of the research landscape on nonprecious materials for plastic waste pyrolysis. By identifying the key trends, authors, institutions, and keywords, this study offers insights into the current state of the research in this field and can serve as a useful reference for researchers and practitioners interested in plastic waste management and circular economy.

Hou et al. conducted a knowledge-map analysis of percutaneous nephrolithotomy (PNL) for urolithiasis, as published in the Urolithiasis journal [12]. PNL is a minimally invasive surgical procedure used to remove kidney stones and has become a common treatment option for urolithiasis. The authors used bibliometric analysis to analyze the knowledge map of PNL research, including the co-occurrence of keywords, authors, institutions, and countries in the publications. The study revealed the research hotspots, knowledge trends, and collaborations in the field of PNL. The authors also identified the most influential authors, institutions, and countries in this area of research, providing insights into the global landscape of PNL research.

This knowledge-map analysis by Hou et al. provides a comprehensive overview of the research landscape of PNL for urolithiasis. By identifying the research hotspots and trends, as well as the key contributors and collaborations, this study offers valuable insights into the current state of the literature and can help researchers and clinicians to identify important research directions in the field of PNL.

In a different field of medicine, Kirubalingam et al. conducted a bibliometric analysis of trends in otolaryngology publications, specifically focusing on articles published in the Journal of Otolaryngology - Head & Neck Surgery [7]. Otolaryngology is a medical specialty that deals with the diagnosis and treatment of conditions related to the ears, nose, throat, and neck. The authors analyzed the publications in this journal over a 9-year period to identify the publication trends, including the publication volume, authorship patterns, research topics, and citation trends. The study revealed the most productive countries, institutions, and authors in the field of otolaryngology research, as well as the most frequently cited articles and research topics.

This bibliometric analysis by Kirubalingam et al. provides valuable insights into the publication trends and research topics in the field of otolaryngology. By analyzing the publication volume, authorship patterns, and citation trends, this study highlights the key contributors and research directions in the field, providing a comprehensive overview of the literature published in a specific otolaryngology journal.

# **3 OBJECTIVES**

- 1. In research on androgenetic alopecia, analyse word dynamics year-by-year to spot variations in word usage, frequency, and context over a ten-year period.
- 2. Create networks of co-occurring terms and keywords in the study of androgenetic alopecia, then analyse the network's features to find hidden correlations and patterns.
- 3. Through the analysis of keyword, topic, and co-occurring terms for frequency and distribution, it is possible to pinpoint important research issues and gaps in the study of androgenetic alopecia.

4. Spread the results of the 10-year trend study to a large audience, including stakeholders and policymakers, by effectively visualising and communicating findings using data visualisation tools, infographics, and reports.

## **4 METHODOLOGY**

R programming is used to get pertinent data from PubMed databases. In order to find scholarly publications, this may include conducting a database search. R programming is used to clean and pre-process the collected data as necessary. A number of procedures are included in the bibliometric analysis utilising R programming (version-4.3.0) and biblioshiny packages.

To conduct bibliometric analysis on the gathered data using biblioshiny, an R programme for bibliometric visualisation and statically analysis. To investigate the connections and trends in the data, interpret the results of the bibliometric study and derive important conclusions from the information. Validating the findings of bibliometric analysis by utilizing appropriate statistical techniques.

The search criteria for the bibliometric study were "androgenetic alopecia" in the title or abstract, "English" as the language of publishing, "journal article" as the form of publication, and publications released between January 1, 2013, and December 31, 2022. By doing this, it was made sure that the analysis was limited to recently published, excellent, peer-reviewed studies on androgenetic alopecia. These criteria were used in the analysis to capture pertinent papers and trends in the area, and to provide a thorough overview of the scholarly literature on androgenetic alopecia.

For example: "androgenetic alopecia"[Title/Abstract] AND "english"[Language] AND "journal article"[Publication Type] AND 2013/01/01:2022/12/31[Date - Publication]

### **5 DATA ANALYSIS AND INTERPRETATION**

From Table 1 & Figure 1, the data used for this analysis spans the years 2013 through 2022 and consists of 1107 documents from 313 sources, including books and periodicals. The average age of the documents is 4.62 years, and the annual growth rate is 8.27%. The documents' content lists 1889 Author's Keywords and 1282 Keywords Plus, which represent the keywords that writers chose to characterise their research. The records list a total of 4057 writers, with 53 entries having just one author. With an average of 5.27 co-authors per document is observed.

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2013:2022
Sources (Journals, Books, etc)	313
Documents	1107
Annual Growth Rate %	8.27
Document Average Age	4.62
Average citations per doc	0
References	1
DOCUMENT CONTENTS	
Keywords Plus (ID)	1282
Author's Keywords (DE)	1889
AUTHORS	
Authors	4057
Authors of single-authored docs	53
AUTHORS COLLABORATION	
Single-authored docs	67
Co-Authors per Doc	5.27
International co-authorships %	0
DOCUMENT TYPES	
biography	1
case reports	14
clinical study	1
clinical trial	14
clinical trial, phase i	1
clinical trial, phase iii	2
clinical trial, phase iv	1

Table 1 Study main information

comparative study	24
controlled clinical trial	2
dataset	1
evaluation study	2
guideline	1
journal article	1029
meta-analysis	2
multicenter study	3
observational study	1
randomized controlled trial	3
review	3
systematic review	2





A constructive trend is indicated by an increase in the number of papers published from 68 to 78 between 2013 and 2014. Only 68 papers were published in 2015, a sign of a plateau or a little decline. A slight growing trend was evident in 2016 with a small increase to 71 articles. The most notable growth occurred from 2016 and 2017, when there were an additional 99 articles, indicating a significant growth trend. 111 articles were published in 2018, continuing the trend of upward growth.

# 5.1 Words Mining

A bibliometric analysis that examined the presence and frequency of certain phrases connected to hair loss and treatment outcomes appear to have produced the list of words that is supplied below. A quantitative research technique called bibliometric examines patterns and trends in published literature by looking at word usage and frequency. As shown in Figure 2.



Figure 2 Top ten most frequently used words

In this instance, the study most likely involved the evaluation of a sizable corpus of scientific literature, including articles, research papers, or other pertinent works on the subject of alopecia and hair loss. The words on the list are those that appear the most frequently in the literature, showing their relative prominence and significance in the area.

The usage of the word "humans" suggests that the study's main focus was on studies involving people as opposed to animals or other living things. In relation to the subject of hair loss, the phrases "alopecia," "male," "female," "adult," "hair," "middle-aged," "treatment outcome," "hair follicle," and "minoxidil" are all used. "Alopecia" is a medical term for hair loss, and "minoxidil" is a common medicine used to treat hair loss.

These phrases appear frequently in the bibliometric study, indicating that they are frequently used and might have an impact on alopecia research. According to reported treatment outcomes, the study may have sought to uncover trends, patterns, and correlations between these terms, such as the prevalence of hair loss in various age groups (e.g., adults, middle-aged people), or the efficacy of therapies (e.g., minoxidil).

The study probably sought to offer insights into the alopecia and hair loss research landscape based on the frequency of particular words used in pertinent literature, which can aid researchers in better understanding the current state of research in the field and identify areas for additional investigation.

# 5.2 Dynamically Words Moving



Figure 3 Top ten most frequently used words

From 54 in 2013 to 758 in 2022, the human appears to have grown steadily, which may reflect a growing research or rising interest (Figure 3). The prevalence of alopecia may be rising, or there may be more attention being paid to this condition in relation to source clustering or author productivity, as seen by the general higher trend in alopecia instances, which increased from 49 in 2013 to 688 in 2022.

Both genders (Male and Female) may be relevant to the subject of source as evidenced by the increasing trend in both the number of men and women over time.

Adults and people in their middle aged are becoming more predominant, which suggests that they could have a big impact on author productivity. The patterns in the variables relating to hair, hair follicles, and minoxidil consumption over time indicate probable changes in the particular characteristics author output under reflection. The statistics on treatment outcomes fluctuate with time, which could be a sign of changes in treatment efficiency or results in terms of bibliometric analysis.

### 5.3 Topic Trend



Figure 4 Top ten most frequently used words

The data form Figure 4 interpretations provide details on a range of issue trends and occurrences. "Azasteroids" frequently appears between 2013 and 2014, whilst "Diagnosis, differential" gradually increases from 2013 to 2016. While "Hyperandrogenism" was frequently noticed between 2014 and 2018, "Phytotherapy" exhibited an upward trend during that same time. The term "severity of illness index" is most frequently used and shows an upward trend between 2015 and 2020.

It has changed throughout time how frequently "Surveys and questionnaires" and "Genetic predisposition to disease" are conducted. Between 2015 and 2019, the terms "adult," "middle-aged," and "young adult" are used regularly. The prevalence of "Male," "Hair follicle," "Finasteride," "Humans," "Alopecia," and "Female" fluctuates between 2016 and 2020. There are some variations in "Minoxidil" and "Alopecia areata" occurrence between 2018 and 2021.

This bibliometric analysis can also give a more comprehensive picture of the demographics and traits of the research population, including the age categories ("Adult," "Middle aged," "Young adult"), gender ("Male," "Female"), and interventions or therapies ("Finasteride," "Minoxidil") under study. This knowledge can help drive future research efforts, point out prospective intervention areas, and help develop healthcare plans that are tailored to the needs of particular groups. Moreover, by spotting patterns, trends, and evolving research interests in a particular area throughout time, analysis might increase our understanding of science. This data can act as the basis for developing hypotheses and conducting more research projects. By giving representatives, monitoring organizations, and funding organisations data-driven insights, the analysis can also support evidence-based decision making and policy adjustments. In accordance with the discovered research trends and interests, it can aid in determining research priorities, allocating resources, and forming plans and procedures. This bibliometric study offers several advantages, including insight generation, decision-making support, scientific knowledge advancement, and future research direction guidance in the area of interest.

#### **5.4 Co-Occurrence Network**

In a term co-occurrence network for bibliometrics, this looks to be a table or list of nodes (keywords or terms), together with the accompanying cluster assignments, betweenness centrality, closeness centrality, and PageRank values. There are multiple columns in the Table 2.

Node, the specific term or keyword in the co-occurrence network is defined. The cluster assignment of the term or keyword in the network denote as cluster here. Closeness, the closeness centrality value, which is a measure of how closely connected a term or keyword is to other terms or keywords in the network.

PageRank, the PageRank value, which is a portion of the importance or centrality of a term or keyword in the network based on the concept of random steps. These values are used to analyse and assess the centrality and importance of each term or keyword in the term co-occurrence network, which can provide insights into the relationships and patterns among the terms or keywords in the bibliometric data. The betweenness centrality score is an indicator of the frequency with which a term or keyword acts as a link along the shortest route between other terms or keywords in the network.

Table 2 Co-occurrence Network								
Node	Cluster	Betweenness	Closeness	PageRank				
hair follicle	1	6.925224395	0.018867925	0.02699581				
animals	1	1.410036578	0.013888889	0.01325049				
androgens	1	0.32146174	0.014492754	0.00849303				
receptors, androgen	1	0.837521177	0.014705882	0.00925615				
mice	1	0.16043895	0.012658228	0.00792028				
skin	1	0.095313228	0.013333333	0.00619316				
signal transduction	1	0.066611381	0.012987013	0.00602147				
testosterone	1	0.078133684	0.012987013	0.00604422				
dihydrotestosterone	1	0.097959345	0.013333333	0.00622343				
cells, cultured	1	0.038909514	0.0125	0.00570192				
humans	2	143.9319161	0.020408163	0.10884467				
alopecia	2	121.1504869	0.020408163	0.10345088				
male	2	63.82704915	0.020408163	0.08013735				
female	2	27.75294547	0.020408163	0.05578458				
adult	2	24.75950655	0.019607843	0.05622055				
hair	2	12.85828733	0.019230769	0.04282205				
middle aged	2	12.58270049	0.019230769	0.04221905				
treatment outcome	2	5.113842217	0.017241379	0.03480038				
young adult	2	6.954564656	0.019230769	0.03225043				
scalp	2	2.869777884	0.017857143	0.02265387				

2	0.419883381	0.014705882	0.01536381
2	1.76164219	0.017241379	0.0176065
2	0.314576852	0.014705882	0.01176566
2	0.776955036	0.017241379	0.01506513
2	0.34847566	0.015151515	0.01250569
2	0.53903331	0.015625	0.01243293
2	0.288976887	0.014492754	0.01292548
2	0.191774032	0.01369863	0.00993342
2	0.073350773	0.013888889	0.00942113
2	0.266846533	0.014492754	0.01059755
2	0.271474824	0.014084507	0.00956639
2	0.042247201	0.013513514	0.00794242
2	0.048895505	0.013513514	0.00839554
2	0.094294702	0.013157895	0.00750583
2	0.021974818	0.012820513	0.00730828
2	0.071996569	0.012987013	0.00621636
2	0.032020319	0.012820513	0.00567652
2	0.01629215	0.012987013	0.00671502
2	0.016074546	0.012345679	0.00584621
2	0.031211271	0.012820513	0.00644629
2	0.023301298	0.013333333	0.00696905
2	0.05070329	0.01369863	0.00736248
3	3.612124447	0.01754386	0.02622392
3	3.642270672	0.017857143	0.02244875
3	1.872341575	0.017241379	0.01651948
3	1.042701011	0.016129032	0.0153487
3	0.091581807	0.013333333	0.00855244
3	0.063573716	0.013888889	0.00810898
3	0.108989247	0.013513514	0.00705877
3	0.031729606	0.01369863	0.00688749
	2 2 2 2 2 2 2 2 2 2 2 2 2 2	2       0.419883381         2       1.76164219         2       0.314576852         2       0.776955036         2       0.34847566         2       0.53903331         2       0.288976887         2       0.191774032         2       0.073350773         2       0.266846533         2       0.271474824         2       0.042247201         2       0.094294702         2       0.071996569         2       0.01629215         2       0.01629215         2       0.016074546         2       0.05070329         3       3.612124447         3       3.642270672         3       1.872341575         3       0.063573716         3       0.108989247         3       0.108989247	2       0.419883381       0.014705882         2       1.76164219       0.017241379         2       0.314576852       0.014705882         2       0.776955036       0.017241379         2       0.34847566       0.015151515         2       0.53903331       0.015625         2       0.288976887       0.014492754         2       0.191774032       0.01369863         2       0.073350773       0.01388889         2       0.266846533       0.014492754         2       0.271474824       0.014084507         2       0.271474824       0.013513514         2       0.042247201       0.013157895         2       0.021974818       0.012820513         2       0.021974818       0.012820513         2       0.016074546       0.012345679         2       0.031211271       0.012820513         2       0.032020319       0.01333333         2       0.05070329       0.01369863         3       3.612124447       0.01754386         3       3.642270672       0.017857143         3       1.872341575       0.017241379         3       1.042701011       0.0

For various nodes and clusters, the table gives numerical values for each of these measurements. Depending on the precise context and study subject under investigation, these data will need to be interpreted. However, a few broad conclusions that may be drawn from the data are as follows:

In comparison to cluster 2, cluster 1 has lower values for betweenness, proximity, and PageRank, indicating that its nodes may be less central or significant in the network.

When compared to other nodes in cluster 1, several nodes, including hair follicles, animals, and androgens, have greater values for betweenness, proximity, and PageRank, indicating that they may be more central or significant within cluster 1.

Nodes in cluster 2 exhibit substantially higher values for betweenness, proximity, and PageRank compared to nodes in cluster 1, suggesting that these nodes may be more central or significant in the entire network. These nodes include humans, alopecia, male, female, and adult. Humans, alopecia, and middle-aged nodes, for example, have relatively high scores for betweenness, proximity, and PageRank, indicating that they may be important nodes in the network. Other variables in the data, such as treatment outcome, sickness severity index, and risk factors, may be important for comprehending the subject of the research. As shown in Figure 5.



Figure 5 Co-occurrence Network

# **6 CONCLUSIONS**

Ultimately, during a ten-year period, the examination of androgenetic alopecia studies using bibliometric and word mining approaches yielded insightful results. Researchers have been able to make inferences about the evolution of research trends and goals in this field by tracking changes in word usage, frequency, and context across time. The construction of networks of co-occurring terms and keywords has allowed researchers to uncover hidden connections and patterns that relate study themes and concepts together in new ways.

Additionally, the identification of significant research topics and prospective gaps in the study of androgenetic alopecia has been made possible by the analysis of keyword, topic, and co-occurring phrases for frequency and distribution. Researchers and decision-makers can use this data to identify areas that need further research and development, which can guide future research priorities and money allocation.

The 10-year trend study's conclusions must also be successfully communicated to a wide audience, including decisionmakers and stakeholders. Making use of infographics, reports, and data visualisation tools can help display the findings in a way that is both aesthetically pleasing and approachable, allowing for more widespread use and distribution of the results.

The application of word mining and bibliometric analyses in the study of androgenetic alopecia has provided valuable insights into research trends, correlations, and potential research gaps. These findings can contribute to advancing the understanding and treatment of androgenetic alopecia, and can inform future research and strategy judgements in this field. Effective communication of these findings to diverse applicants is essential for maximizing the impact and relevance of the research outcomes.

# 7 LIMITATIONS

It is crucial to recognise the limits of a 10-year trend analysis of androgenetic alopecia utilising word mining and bibliometric methods based on PubMed data. These might include a possible bias in the keyword selection process based on the terminology used in PubMed publications, a lack of coverage of research articles published elsewhere, and a potential omission of unpublished or unreviewed literature.

The reliability and accuracy of the data that was taken from PubMed may potentially have an effect on the results. When interpreting the conclusions based purely on PubMed data, care should be taken to keep them within the parameters of the PubMed database. To gain a more thorough understanding of the scientific landscape of androgenetic alopecia, complementary data sources and research methodologies may be required.

# **COMPETING INTERESTS**

The authors have no relevant financial or non-financial interests to disclose.

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