International Journal of Biological Macromolecules 306 (2025) 141565

Contents lists available at ScienceDirect

International Journal of Biological Macromolecules

journal homepage: www.elsevier.com/locate/ijbiomac

Review

Using network analysis and large-language models to obtain a landscape of the literature on dressing materials for wound healing: The predominance of chitosan and other biomacromolecules: A review

Jaromir Klarak [a], Ana Caroline M. Brito [b], Luan F. Moreira [c], Filipi N. Silva [d], Diego R. Amancio [b], Robert Andok [a], Maria Cristina F. Oliveira [b], Maria Bardosova [a], Osvaldo N. Oliveira Jr. [c,*]

[a] Slovak Academy of Sciences, 845 07, Bratislava 45, Slovak Republic
[b] Institute of Mathematical Sciences and Computing, University of Sao Paulo, Sao Carlos, SP 13566-590, Brazil
[c] Sao Carlos Institute of Physics, University of Sao Paulo, Brazil
[d] Observatory on Social Media, Indiana University, Bloomington, IN 47408, United States

ARTICLE INFO

Keywords:
Wound healing
Dressings
Network analysis
Natural language processing
Large-language models

ABSTRACT

We present an overview of the literature on dressing materials for wound healing, combining network analysis and natural language processing using large language models. Contributions to this field come from a variety of research areas and journals, so we employed multiple strategies for searching the *OpenAlex* database to ensure that the most relevant papers were covered, while also focusing on the specific topic of interest. Citation networks were created from the retrieved papers, identifying clusters that represent major topics. Starting with broad searches on 'wound' and 'wound healing' we refined the focus to dressing materials by incorporating expert knowledge into the analysis. This approach also allowed for a comparison with fully automated analyses. The resulting landscape shows significant growth in this area in recent years, with most contributions coming from the Northern Hemisphere, particularly China and the USA. The most commonly used materials include gauze, hydrocolloids, chitosan-based hydrogels, foams, alginates, hydrofibers (e.g., those containing nanomaterials such as silver nanoparticles), composites, biomaterials, and skin substitutes. Research primarily focuses on the antibacterial properties of these materials and their application in treating burn-related wounds, which, along with diabetes, are common causes of chronic wounds.

1. Introduction

Literature surveys have become an essential construct of scientific research for several purposes, from guiding the choice of research themes to assisting in data analysis. Perhaps the most frequent purpose is to obtain a perspective landscape of a research area, as it is done in many review papers and even journals dedicated to reviews of the literature. While in the past such surveys could be done by exploring a limited number of journals that covered a specific topic, this is no longer feasible owing to the large increase in the number of journals and papers published, coupled with the increasingly multidisciplinary nature of research [1]. This scenario added substantial complexity to tasks of processing knowledge and establishing a foundation for future scientific directions, motivating a new field of research, the so-called "science of science" [2]. Potential solutions to process the scientific literature are today mostly based on statistical and computational methods, including natural language processing combined with network analysis [3] and machine learning [4]. Complex networks have been used in the area of "Science about Science" [5,6] with the basic premise to unify works, authors, and similar entities into communities (i.e., clusters of densely connected entities) based on their logical connections. Research contributions also addressed methods to increase the accuracy of community detection, examining the relationships between link density and network nodes [7,8] exploring network geometry [9], and identifying emerging trends [10].

With regard to obtaining landscapes of research areas and journal contents, network analysis has been applied to investigate the field of photonic crystals [11] where communities were created in a citation network. The same strategy was used to describe the main areas covered in scientific journals of chemistry and materials sciences [3] and

* Corresponding author.
E-mail address: chu@ifsc.usp.br (O.N. Oliveira).

https://doi.org/10.1016/j.ijbiomac.2025.141565
Received 16 December 2024; Received in revised form 15 February 2025; Accepted 26 February 2025
Available online 26 February 2025

elaborating on the history of a journal in terms of how the research topics addressed in the published papers evolved [12]. An overview of papers from the *Web of Science* database in applications of artificial intelligence was provided with networks serving as foundational material for e-learning in the medical field [13]. Visualization of these networks has been made with tools such as *Helios-web* [14], *VOSviewer* [15,16] and *Gephi* [17].

Our purpose here is to obtain a landscape for the literature on dressing materials employed in chronic wound healing, which is an essential topic in our European Project SWORD (*Smart Wound Monitoring Restorative Dressings*). Some related work exists, which is worth mentioning. A bibliometric analysis of the relationship between macrophages and wound healing was made by Guo et al. [18]. Keywords related to wounds, such as wound heal*' and 'wound reconstruct*', were searched in the WoS database, resulting in 4654 papers, of which 4296 were further processed. The central themes in the publications were wound healing, macrophages, and inflammation. Another study processing articles from the *Web of Science* (WoS) database examined trends in the use of nanoparticles in wound healing [19]. It illustrated the exponential growth of publications, with results presented using the *VOSviewer* tool. The total number of processed publications was 2076, featuring keywords such as 'wound healing', 'nanoparticle', 'antibacterial', 'hydrogel', and 'chitosan'. The topic 'chronic wounds' was investigated with data from the *WoS* database and networks created using *VOSviewer* [20], while the use of nanomaterials in wound healing was conveyed with word cloud representations [21]. Publications on *Diabetic Foot Ulcers* were analyzed using *CiteSpace* [22]. It is worth noting that the strategies mentioned handled a few thousand papers in each case. While these are large numbers to allow for manual evaluation, they may be insufficient to encompass a broad field of interest. Besides, the visual representations employed are limited in their capacity to express the major topics and sub-topics and their relationships.

There is abundant literature on chronic wounds, as evidenced by numerous recent reviews [23–30]. Hydrogels based on chitosan are among the most important dressing materials for such wounds [31–37], as will be confirmed in this paper. Research explores the antibacterial properties of these materials [38,39] and their multifunctional role in the wound healing process [40]. Broader studies investigate the use of supporting materials, such as nanoparticles or other biocompatible substances, to enhance wound healing [41–45] The term chronic wound first appeared in the literature in the 1950s, but it has been remarked [46] that in 2017 there was still no consensus regarding an exact definition of this condition. The same is true of the terms referring to the clinical specialty that studies wounds and the medical specialty of physicians who treat patients suffering from chronic wounds. The terms coined were 'Woundology' [47] and 'Vulnerology' [48], but neither was met with wide acclaim, probably because a multidisciplinary approach is necessary to deliver adequate care to these patients. Optimally, they are treated in wound care centers or clinics and, if such facilities are not available nearby, patients depend on referrals from their general practitioner (GP) or on the doctors treating the condition that originated the chronic wound development – trauma, vascular disease, diabetes, burns, etc. Chronic wounds are on the rise worldwide and present a global concern. They affect the quality of life of patients and their families while placing an increasing burden on medical systems and society as a whole. There are estimates that, as the world population ages, on average 2.5 % of them will experience chronic wounds during their lifetime [49]. In China, chronic wounds presently affect nearly 50 million people annually, motivating the introduction in 2019 of a new third-level discipline of clinical medicine named 'Wound Repair' [49]. Besides developing new medical therapies, providing better care depends on ongoing research activities in other scientific disciplines, namely Physics, Chemistry and Materials Sciences, which pursue the development of functional and composite materials that could facilitate and speed up the healing process.

In this paper, we introduce varied strategies to obtain a landscape of dressing materials used in chronic wound healing, using network analysis and natural language processing in association with large-language models. This allows us to address the challenges posed by the increasing volume of research in this field. With such combined strategies, we hope, first, to get a rough estimate of the number of papers published related to the topic and then provide a bird's eye view of the field, even if tens of thousands of papers have to be covered. In addition to standard citation networks, we incorporated content-similarity to focus on the topic of interest, thus generating a kind of similarity-enhanced citation network. Furthermore, in order to avoid missing potentially relevant materials, we departed from rather generic searches in the *OpenAlex* database [50] and adopted strategies to focus on the topic by incorporating knowledge from a human expert in generating the networks.

2. Methodology

We conducted a comprehensive search to identify papers related to applications of materials science for healing chronic wounds, trying to ensure that no relevant papers would be neglected. Thus, we opted to perform different types of searches. We performed queries with the bigram 'chronic wound' and combined both terms, searching for 'chronic' and 'wound'. Since we feared these search queries, although broad in scope, might still miss relevant papers, we executed an even broader query upon searching for the term 'wound'. Papers were retrieved along with citation data, publication journals, and information about authors and their affiliations. We then built different types of citation networks with the vast chunks of papers retrieved in different conditions, employing alternative approaches to identify the potentially relevant communities, i.e., clusters of densely connected papers addressing topics in themes related to our focus of interest.

We conducted an initial analysis using the approach described in our previous paper [11] in which we generated a landscape of the scientific literature on a given theme by identifying the network communities (or clusters, we shall use both terms interchangeably along the text) and the major topics addressed in their papers [3,11] This approach is detailed in Section 2.3. While in the original method [11] clusters and topics are identified in an automated manner, considering measurements of cluster size and term frequency, in the current investigation we introduce a variation in which the most relevant clusters are identified considering the presence and relative importance of a pre-defined set of informative keywords in the documents in the cluster. This procedure is described in Sections 2.2 and 2.4. In yet another variation of the original method, we created a modified paper connectivity network to consider the paper's thematic contents in establishing the network links. This was done for a subset of papers that had already been selected as related to the topic. The method utilizes a language model to generate embeddings from the paper abstracts and computes the pairwise cosine similarities of the resulting vectors to obtain a numerical value indicating the similarity between the corresponding papers. Only pairs of papers with high similarity scores are connected, creating a new network in which connections are based on content similarity. Again, clusters are identified in the resulting network, and in the final step the clusters most relevant to 'dressings for chronic wounds' are identified. This approach is detailed in Section 2.5. The results are presented in Section 3 while a comparison of the different approaches is made in the Conclusions in Section 4.

2.1. Collecting data

Paper collection was conducted using the *Application Programming Interface* (API) available for the *OpenAlex* repository [50]. We searched the obtained repository, conducting queries using the term 'chronic wound' or, alternatively, 'chronic' and 'wound' combined. These queries retrieved ca. 22,022 and 24,019 papers, respectively. For the more general search using 'wound' only, data collection was done in March 2023, when the *OpenAlex* repository included nearly 246 million articles and 90 million authors and related attributes. The query employing the keyword 'wound' in any context retrieved 279,601 articles by 805,410 authors, with a total of 1,130,752 citation connections identified. We downloaded information from these papers, including titles, abstracts, publication year, citation numbers and cited papers, journals, and publishers [51]. We also created an author dataset, keeping the paper titles, author names, institutions, and countries. Fig. S1 in the Supporting Information shows the annual number of papers from 1920 to 2022, revealing a significant growth after around 2000. In the last decades, most contributions were authored by researchers in the *United States of America* (USA) and China, as shown in Figs. S2 and S3. Fig. S4 in the Supporting Information shows the distribution of articles per publishing companies.

2.2. Identifying relevant keyterms

Three strategies were employed to identify highly relevant keyterms for the topic of dressings for chronic wounds, all of which operate on the giant components of citation networks constructed from the collection of papers. In the first, we just applied the procedure adopted in [11], in which relevant topics are determined automatically with no manual interference. In the second, we conducted a manual analysis of the literature to identify empirically a set of highly relevant keywords commonly associated with materials and processes (or procedures) in this context. This effort resulted in 11 keywords (or stems of keywords), six of which are related to healing wounds (processes and procedures), and the remaining five are associated with materials. The selected keywords (and stems) are: *acute*, *burn*, *chitosan*, *chronic*, *collagen*, *dressing*, *exudat*, *hydrogel*, *material*, *therap*, *nanoparticle*. The third strategy used a large language model based on transformers, namely the *KeyBERT* model [52,53] to identify relevant keywords. We employed *KeyBERT* to generate keywords from the paper abstracts and determine their similarity to the selected specific keywords. The similarity is computed as the normalized dot product between the two embedding vectors representing the extracted keywords and the abstract's content (i.e. cosine similarity). We extracted 30 keyterms from each abstract using single words, two-word combinations, and three-word combinations (i.e., we used n-grams with $n = 1, 2, 3$). This approach resulted in 90 keyterms per abstract. The inclusion of two-word and three-word terms is important to capture the context in which terms occur.

2.3. Building citation networks with the query 'chronic' and 'wound'

In the method in [11], the papers of a given corpus are connected into a network based on their citation patterns, and a community detection algorithm is run to partition the network into clusters of densely connected nodes. In building the citation networks, two papers X and Y are connected with a link if (i) X cites Y, or vice-versa; (ii) X and Y both cite Z (where Z is also in the corpus). The *InfoMap* community detection method, based on the map equation [54], is employed to identify the network clusters. Clusters are identified on the largest connected component of the network (its giant component), and the remaining smaller connected components are ignored. Given the clusters and their associated papers, frequent terms in paper titles and abstracts can be identified and related to relevant topics addressed by the papers. Terms may be single words, bigrams or trigrams, and term relevance is estimated based on how frequently it occurs within a cluster in comparison with its occurrence outside, i.e., in the other network clusters. Thus, keywords are assigned importance values and ranked, and the most relevant ones are selected to summarize the cluster's topical content, identifying the most salient themes in each cluster. The largest clusters in the network can be inspected using the *Helios-web* visualization platform [14].

The clusters were also assigned titles generated by *ChatGPT* using the *OpenAI* API and the model *GPT-4o mini*. The input for this task consisted of prompts with the 100 most relevant keywords (single words, bigrams or trigrams) of each cluster and their computed importance values.

2.4. Building citation networks with the query 'wound'

We applied the method described in [11] on the largest component of the network generated with the corpus retrieved with the more general search using solely the term 'wound*'. Then, we assessed empirically the thematic relevance of its individual clusters. As expected, not all clusters were relevant, and we conducted an iterative process of refining the network, which is illustrated in Fig. 1. The clusters were examined based on the occurrence and significance of the keywords in clusters, discarding those with thematic content not of interest (e.g., clusters addressing topics not of interest, or with themes too diverse or not sufficiently informative). We preserved the only relevant clusters to our study. This cycle is repeated, running the community detection algorithm once again, until the conditions are met of finding a sub-set of potentially representative clusters (in terms of topical content). Once a satisfactory network is obtained, its clusters are assessed in relation to the relative importance of the 11 target keywords (see Section 2.2), and the ten most representative ones are identified for further analysis.

By preserving the related clusters and discarding the unrelated ones we generate more focused networks, which can be gradually refined according to our target. In this sense, we managed to combine the expertise of a scientist studying the field with the massive capacity of computational systems to process text from literature.

2.5. Building content similarity networks

We realized that the method used in [11] often yielded clusters highly unbalanced in size. This is not desirable, as identifying meaningful relevant terms in very large or very small clusters of papers is not effective. This motivated an alternative strategy that restricts the connections to consider paper content similarity, i.e., papers are linked not only based on their citation patterns, but also considering the degree of similarity of their textual content. For this, vector embeddings of the papers have been created with the *SciBERT* language model [55], from which pairwise content similarities can be computed. Thus, two papers remain connected in the resulting network only if their pairwise similarity exceeds a selected threshold, which we empirically set to 0.85. Then the same strategy of identifying the network clusters is applied, as well as identifying the clusters highly related to the selected keywords, to identify the clusters most related to our focus of interest.

3. Results and discussion

In this section we present the relevant networks obtained with the three aforementioned approaches, we analyze them and discuss the findings. We also present a short summary of the demographics of the contributors in the field regarding the major institutions and their distribution.

3.1. Analysis of citation network with the query 'chronic and wound'

The sub-network formed by the major clusters identified in the giant component of the initial network created with the 24,019 papers retrieved with the query 'chronic' and 'wound', as identified by the standard method we used in [11], is shown in Fig. 2. Table 1 informs the cluster sizes and the topic titles provided by *GPT-4o mini*, which was prompted with the keywords identified by the method, ranked by importance. This network is similar to the one obtained with the 22,022 papers retrieved with the query 'chronic wound', which therefore will not be discussed further. The largest cluster in Fig. 2 (Cluster "A", shown in blue) includes over 9300 papers, being significantly larger than all the other ones. It is related mostly to materials used for wound healing, which normally have antibacterial effect. A much more refined analysis can be done by visualizing the 3D version of the network in the *Helios-web* platform [14] (available at http://server1.phys.eu:8080/docs/example/index.html?network=network_v5-BASIC__chronic_and_wound).

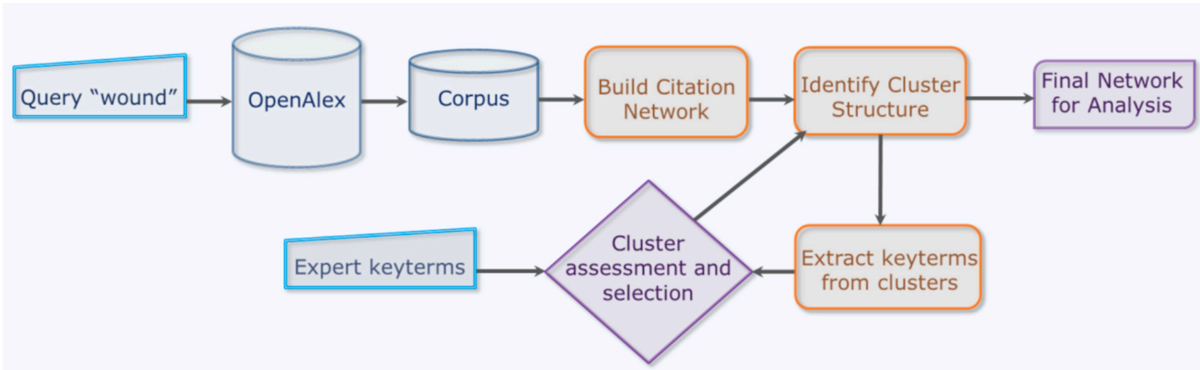

Fig. 1. Steps of the methodology for analyzing the networks obtained with the query 'wound*'.

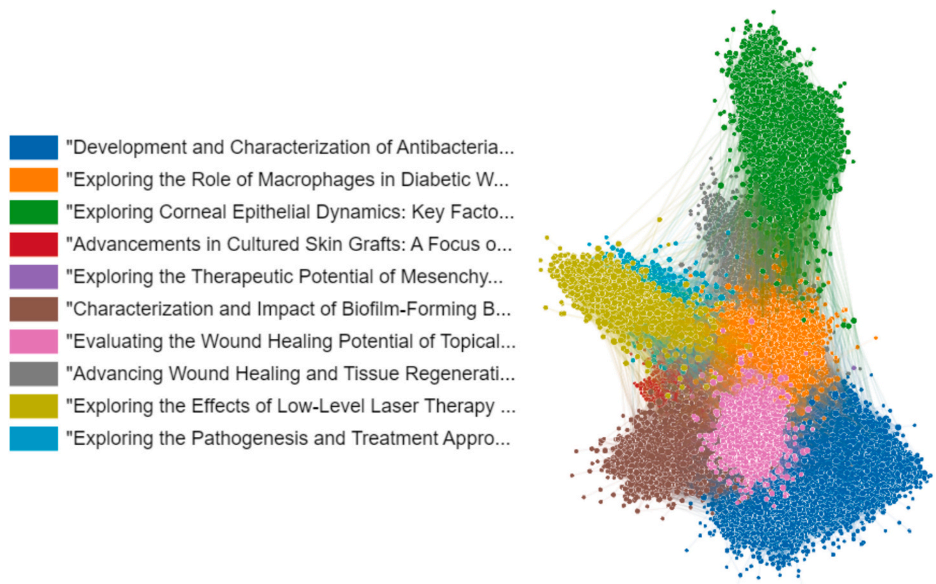

Fig. 2. The 10 clusters in the giant component of the *network_v5-BASIC_chronic_and_wound* generated with the method from [11] for the papers retrieved with the query 'chronic' and 'wound'. This network has 24,019 nodes and 256,125 edges.

Table 1
Clusters and their titles obtained in the network of Fig. 2.

Cluster ID	Cluster index &title	Cluster size	Chronic wound	Chronic	Wound	Wounds	Chronic and wound
A	0	9339	101	509	5298	2260	5807
	Title	Development and Characterization of Antibacterial Chitosan-Based Hydrogels for Enhanced Biocompatibility in Wound Dressing Applications					
B	1	3090	31	195	1792	792	1987
	Title	Exploring the Role of Macrophages in Diabetic Wound Healing: Insights into Inflammatory Mechanisms and Therapeutic Targets for Chronic Ulcers in 2023					
F	5	2028	30	123	1240	591	1363
	Title	Exploring Corneal Epithelial Dynamics: Key Factors in Corneal Wound Healing and Regeneration					
C	2	1853	27	127	1151	562	1278
	Title	Advancements in Cultured Skin Grafts: A Focus on Keratinocyte Contributions to Burn Wound Regeneration and Dermal Substitutes					
D	3	1566	15	89	958	407	1047
	Title	Exploring the Therapeutic Potential of Mesenchymal Stem Cells in Skin Wound Healing and Tissue Regeneration					
E	4	1464	13	79	862	393	941
	Title	Characterization and Impact of Biofilm-Forming Bacteria in Chronic Wound Infections: A Focus on *Pseudomonas aeruginosa* and *Staphylococcus aureus*					
I	8	1391	11	85	829	359	914
	Title	Evaluating the Wound Healing Potential of Topical Plant Extracts: Antioxidant and Anti-inflammatory Properties in a Rat Excision Model					
L	11	1217	9	72	713	331	785
	Title	Advancing Wound Healing and Tissue Regeneration: The Role of Platelet-Rich Plasma (PRP) and Its Components					
M	12	1056	15	63	629	310	692
	Title	Exploring the Effects of Low-Level Laser Therapy on Wound Healing: A Comprehensive Study Using Photobiomodulation Techniques in Diabetic Rats					
K	10	1015	19	55	612	260	667
	Title	Exploring the Pathogenesis and Treatment Approaches for Hypertrophic Scars and Keloids: The Role of Fibroblasts and Collagen Dynamics					

The network can be manipulated with the mouse, allowing for zooming in and out, checking the titles of the papers by clicking on the dots (network nodes). The size of the dots can be varied, and search for specific terms can be performed. An inspection of the 3D network reveals that Cluster “A”, on the topic antibacterial chitosan-based hydrogels for wound dressings, is strongly connected to other clusters that include papers concerned with dressings for chronic wounds. For instance, the neighboring clusters are Cluster “B” (in orange) dedicated to macrophages and diabetes-associated wounds, Cluster “C” (in red) related to skin grafts, Cluster “E” (in brown) associated with biofilms and bacteria contamination, and Cluster “I” (in pink). The latter is an interesting one because it is focused on products (mostly natural products) used in wound healing. Other clusters are not as closely connected with the blue one. For example, Clusters “F” and “M” shown in dark green and in lime, respectively, refer mostly to wounds on the cornea and the use of laser therapy for wounds. This looser connection is not surprising, as the dressing materials for skin chronic wounds may not be applicable to the cornea, and laser therapy is a very specific theme. A similar observation can be made of Cluster “L” (in light gray), which focuses on tissue engineering and regeneration, and Cluster “K” (in cyan) associated with scars.

While all the clusters identified in the network in Fig. 2 can clearly be associated with wound healing, one notices that not all of them are specific for dressings or consider the materials used. Furthermore, it is possible that relevant papers are being overlooked owing to the query formulation, a hypothesis that was confirmed in further experiments conducted with collections of papers retrieved with more general queries, as described next.

3.2. Analysis of citation networks (query ‘wound*’)

We built the network connecting the papers that cite each other in the collection of ca. 1,000,000 papers retrieved with the query using solely the word ‘wound’ in any context. The major connected component of the resulting network includes 172,652 papers and is referred to as *network_v1*, which obviously includes a much larger number of papers than with the query ‘chronic and wound’ (ca. 24,000 papers). The occurrence of multiple connected components in such a large network built from real data is expected and can be explained by the recent surge in published papers (see Fig. S1), which are too recent and thus not yet cited, impacting connectivity. We then employed the *Helios-web* platform [14] to visualize and inspect the resulting clusters to identify and select those actually related to chronic wounds. The *InfoMap* algorithm initially identified 3070 clusters in *network_v1*, with a dominant cluster containing 160,482 nodes (from a total 172,652 nodes). At this stage, in view of the number and diversity of clusters, we verified which ones were more related to the original 11 target keyterms. While the frequencies of the 11 keyterms were high in the dominant cluster (Cluster 1), as seen in Table S1 in the Supporting Information, this was not the case in the remaining 3069 clusters. We therefore took this large cluster as the sole content of *network_v2*, on which 47 clusters were identified running *InfoMap* again (details are provided in the Supporting Information). Upon inspecting the 10 largest clusters, we found that two of them were unrelated to chronic wounds: one focused on botanical wounds and the other on gunshot wounds. We excluded these clusters and obtained *network_v3* from the remaining ones, formed by 128,121 nodes. Running *InfoMap* once again yielded 15 clusters identified in *network_v3*, the largest one with 91,930 nodes. Since the remaining 14 clusters did not exhibit a high frequency of the original 11 keyterms, the largest cluster of *network_v3* was taken as *network_v4*, on which 4 clusters have been identified. The largest one, containing 91,616 nodes, became *network_v5-BASIC*, and the remaining 3 were discarded, again because the target keyterms were not highly frequent. Table 2 - 2 provides a description of the five networks. Detailed descriptions of the networks and clusters, including associated keywords, size, and other metrics, are provided in Table S1 in the Supporting Information.

Table 2
Iteration on citation networks to identify relevant clusters and the main parameters.

Network name	No. of nodes No. of edges	No. of clusters	Selected clusters
network_v1	172,652 1,130,752	3070	1
network_v2	160,482 1,114,337	47	1, 2, 5, 6, 7, 8, 9, 10
network_v3	128,121 977,293	15	1
network_v4	91,930 800,096	4	1
network_v5-BASIC	91,616 799,323	2201	Top 10

Fig. 3 shows a visualization of *network_v5-BASIC* with its 10 largest (in number of papers) clusters shown in different colors, with the remaining 2191 clusters shown in light gray. The total number of 91,616 papers is possibly a good indicator of the size of the field in wound healing in the literature. The largest cluster (“A”, shown in blue) is related to hydrogels and chitosan, which confirms the intuition in choosing chitosan as one of the 11 original keyterms. Other clusters include various materials and topics associated with wounds in a variety of contexts. Although this network provides an initial global view of papers related to our topic, further specification was necessary to focus on applications of materials for healing chronic wounds, as detailed next. Indeed, the presence of a cluster related to corneal wound healing (Cluster “F”, in green) indicates that some of the clusters may not be associated with dressing materials for chronic wounds.

Since the goal was to identify in *network_v5-BASIC* the papers focused on chronic wound from the perspective of dressing materials for healing and therapy, we analyzed the importance of the 11 terms related to chronic wound in the clusters. A measure of the importance (I_i) of a keyword in a given cluster can be computed using Eq. (1), as defined elsewhere [56]. (I_i) refers to the frequency of a keyword w in a cluster (N_{ci}) normalized by the cluster size (S_{ci}), from which the frequency of w in all the remaining clusters (N_{outci}), again normalized by the network size (S_{outci}), is subtracted.

$$I_i(\mathrm{w}) = \frac{N_{ci}(w)}{S_{ci}} - \frac{N_{outci}(w)}{S_{outci}} \quad (1)$$

We employed Eq. (1) to compute a metric of the importance for the 11 keywords manually identified on all clusters in *network_v5-BASIC*. We selected the 10 clusters with the 10 highest frequency counts of the sum of the importance values for the first six keywords as the most relevant to the investigation. These are detailed in Table 3 and in Fig. 4. In the network in Fig. 4 one notices some clusters are characterized by keyterms such as *materials*, *chitosan*, *nanoparticles*, *collagen*, *hydrogel*, and others, which we interpret as related to wound treatment and materials employed in such treatments. We take this resulting network, formed by 12,473 nodes and 124,720 connections, as representative of the papers published with a focus on dressings for chronic wounds. The largest cluster, identified as “A”, appears in blue in Fig. 4. The 3D visualization in the *Helios-web* platform (http://server1.phys.eu:8080/docs/example/index.html?network=network_v5-BASIC_FOCUS_GPT) indicates that this dominating Cluster “A” – related to materials employed in wound dressings, especially chitosan-based hydrogels – is closely associated with Cluster “N” (antimicrobial dressings, in green), Cluster “35” (coatings and dressings, in red), and Cluster “86” (exudates, in pink). The second largest cluster, “W” (orange), is associated with burns, and so are Clusters “43” (purple), “70” (brown), “114” (lime) and “235” (in light blue). These clusters are neighbors to each other in the 3D network, and are far apart from Cluster “A”. One could interpret these results as if the hydrogel and chitosan dressings in Cluster “A” are not employed in burn wounds, but this is the not the case because the term *burn* is highly

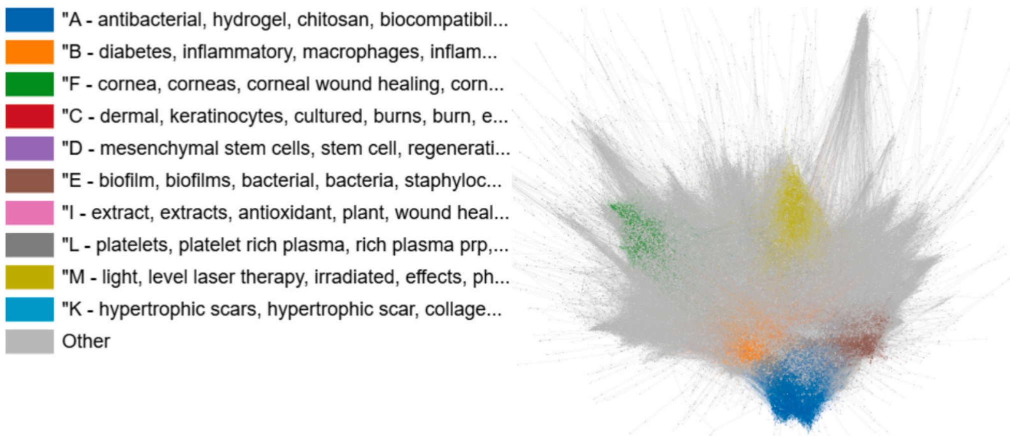

Fig. 3. View of *network_v5-BASIC* formed by 91,616 nodes and 799,323 edges, from which 2201 clusters were identified. The 10 largest clusters are identified and shown in different colors while the remainder of the network is shown in light gray.

Table 3
Counts of keywords in the 10 clusters selected from *network_v5-BASIC*.

Cluster ID	Cluster size	Exudat	Dressing	Therap	Chronic	Burn	Acute
A	9339	644	28,689	6428	3127	3666	330
N	803	74	5048	433	420	3901	162
W	932	11	301	730	49	16,285	186
34	349	130	3165	134	164	638	120
43	331	1	97	69	15	8281	43
70	289	51	15	292	55	4229	115
86	150	714	1939	60	219	25	71
88	140	7	13	67	9	3765	64
114	82	1	7	84	2	2033	9
235	58	0	111	16	0	1518	58

Fig. 4. View of network_v5-BASIC_FOCUS formed by the 10 most relevant clusters of the network in Fig. 3, where relevance was computed based on metrics for the 6 keywords in Table 3. This network has 12,473 nodes and 124,720 edges.

frequent in this cluster. The reason for these clusters related to burn appearing separate from Cluster "A" may be that there is considerable research on burn wound that is not focused on the hydrogel and chitosan dressings. These clusters are nevertheless much smaller than Cluster "A". The term '*exudat*' as an important keyword is most frequent in Clusters "A", "34", and "86", which may seem surprising, as it should also relate to burn wounds. The titles provided by *ChatGPT* for the clusters in Fig. 4 are listed in Table 4. In terms of the size of the specific topic of dressings for chronic wound healing, the largest clusters can be readily recognized as being relevant, which amount to at least 10,500 papers.

The temporal evolution of the topics associated with the clusters of the *network_v5-FOCUS* in Fig. 4 is depicted in Fig. 5. Cluster "A", related to hydrogels and chitosans, dominates along the whole period, as indicated in Figure (a). The evolution of the remaining topics is better observed in Figure (b), in which Cluster "A" is omitted. The relative importance of the clusters, in terms of the number of papers in each one, is illustrated in Figure (c) and (d), highlighting the recent growth in the number of papers in Cluster "A". As for the remaining clusters, one should notice the significant growth of Cluster "43", associated with imaging and burns, while the relative contribution from the other clusters remained practically constant. Perhaps the most important feature in Fig. 5 is revealing that the field of dressings for chronic wound healing is very young, with most papers published after 2015.

Table 4
Titles of the clusters identified in the network of Fig. 4, as suggested by model GPT 4o-mini.

Cluster ID	Cluster title
A	Development and characterization of antibacterial chitosan-based hydrogels for enhanced biocompatibility and drug delivery in wound dressing applications
N	Evaluating the efficacy and toxicity of silver nanoparticle-containing dressings in the management of burn wounds: a comprehensive review of antimicrobial properties and clinical applications
W	Prevalence and antimicrobial resistance of bacterial pathogens in burn wound infections: implications for patient mortality and infection control strategies
{34}	Comparative analysis of moist wound dressings: evaluating hydrocolloid, foam, and gauze for optimal healing environments in superficial and partial thickness wounds
{43}	Noninvasive assessment of burn depth and severity using laser doppler imaging and infrared thermography: a comprehensive evaluation of burn wound healing
{70}	Optimizing nutritional support in severely burned patients: the role of supplementation in enhancing anabolic response, metabolism, and recovery outcomes
{86}	Effectiveness of superabsorbent dressings in managing exudate for chronic wound care: a comprehensive evaluation of current practices and products
{88}	Early excision and grafting in burn care: impact on mortality and outcomes in major burn injuries
{114}	Investigating the impact of oxidative stress on burn wound progression and healing: insights from a rat model of comb burns
{235}	Effectiveness of early cooling interventions in managing pediatric burn injuries: a comprehensive review of recommended practices and outcomes

3.3. Analysis of content similarity networks

The clusters obtained from the co-citation networks are highly unbalanced in size, with a single cluster much larger in size and many small ones, as observed in Table 3 and Figs. 4 and 5. This motivated us to incorporate some analysis of content similarity when building the networks, hoping this might contribute to generating a more cohesive network with more balanced clusters. In particular we wanted to reinforce links between papers that were similar in content (considering the text of titles and abstracts), hypothesizing this strategy may be more effective in capturing papers more strongly related to our target topics. We employed the *SciBERT* [55] language model to create vector representations of the abstracts of papers included in the *network_v5-BASIC*, using as input their titles and abstracts. We then computed the cosine similarity between the vector pairs already linked in the network. The cosine similarity takes values in the range [0,1] indicating increasing levels of content similarity. After some experimentation with different similarity threshold values, we set a minimum threshold of 0.85 for establishing a link between a pair of papers. Our empirical trials with different values for the similarity threshold indicated that values lower than this threshold yielded networks with clusters not very well defined (as an illustration, Fig. S5 in the Supporting Information shows a network generated with a threshold of 0.682, and its clusters). We thus created the content similarity network (*network_v5-SciBERT*) and ran the *InfoMap* algorithm to identify the network clusters. In the sequence, we selected the 10 clusters with the highest importance values associated with the 11 chronic wound keywords, employing the same approach described previously. The resulting network and its 10 most relevant clusters are shown in Fig. 6, featuring clusters for 20,135 papers that are more segregated than those in the network of Fig. 4.

The clusters in *network_v5-SciBERT_FOCUS* are described in Table 5, which highlights an important limitation of our approach. As we restricted the links to papers assessed as highly similar and sought to emphasize clusters strongly related to the relevant words, some of the resulting clusters are very small. Indeed, Clusters “73”, “382” and “2673” have only 11, 4 and 2 papers, respectively, and must be disregarded. The clusters in Fig. 6 have been assigned titles generated by *ChatGPT*, using the procedure mentioned in Section 2, as shown in Table 5. The network has 20,135 papers, more than the network shown in Fig. 4. An inspection of the network at (http://server1.phys.eu:8080/docs/example/index.html?network=network_v5-SciBERT_FOCUS_GPT) reveals that the largest cluster (Cluster “A”, in blue) is related to

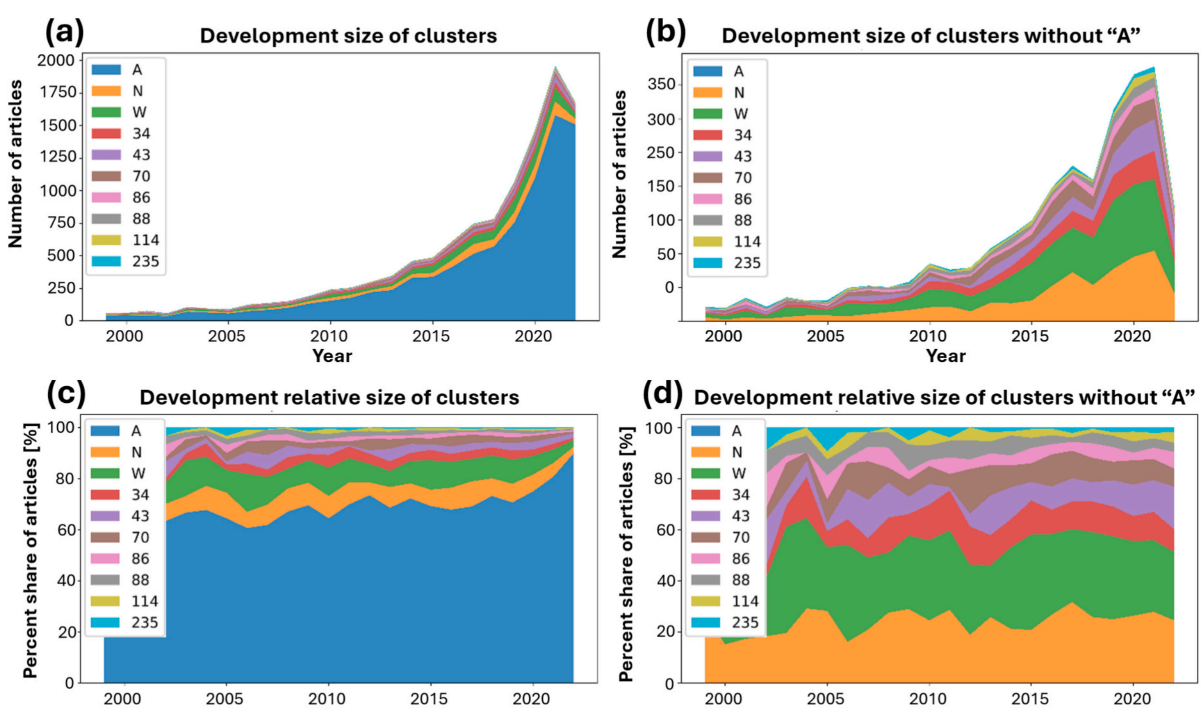

Fig. 5. Temporal evolution of the size (number of papers) of the clusters in the *network_v5_BASIC_FOCUS* (Fig. 4), from 1999 to 2022. (a) Evolution of all clusters. (b) Evolution of clusters after removing predominant Cluster “A”. (c) Relative distribution of papers in each cluster. (d) Relative distribution without Cluster “A”.

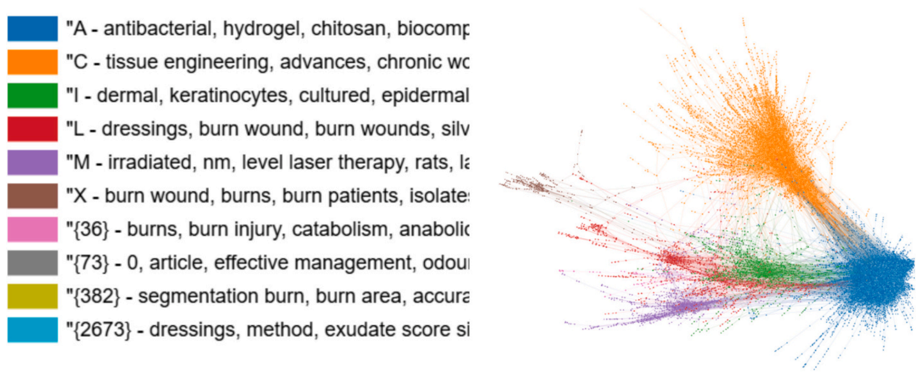

Fig. 6. The *network_v5-SciBERT_FOCUS*. This network has 20,135 nodes and 60,871 edges.

Table 5
Keyword counts in the 10 selected clusters in *network_v5-SciBERT*, in addition to the cluster sizes.

Cluster ID	Cluster size	Exudat	Dressing	Therap	Chronic	Burn	Acute
A	9108	595	23,963	6530	3112	4621	387
C	6990	403	7557	12,713	8718	4919	1241
I	1296	41	1050	654	532	4652	197
L	1274	107	6789	755	585	16,498	324
M	1046	23	257	3640	556	1177	128
X	313	5	106	197	15	5692	25
36	91	14	0	113	6	1501	40
73	11	95	15	0	12	0	0
382	4	0	0	0	0	194	0
2673	2	61	11	5	2	0	0

chitosan-based materials and hydrogels, which are the most important materials employed in the wound healing dresses. This should indeed be expected from the analysis of Fig. 4. The second largest cluster (Cluster "C", in orange) is well separated from the first one, being related to tissue engineering and therapeutic strategies for chronic wound healing. The remaining clusters are much smaller, as informed in Table 5. They are also very specific; for example, Cluster "I" (in green) covers dermal regeneration, particularly for burn wounds. Burn wounds are also prominent in Clusters "L" and "X", while Cluster "M" is related to laser therapy for chronic wounds. It is possible to identify 'chronic wound healing' as the core of the papers covered in all clusters. If one is very strict about identifying dressing materials, however, the total number of relevant papers would be 20,135, corresponding to the four major clusters. The cluster titles provided by *ChatGPT* are listed in Table 6.

While the strategy of restricting the links to connecting papers with similar contents may seem advantageous to obtain highly segregated clusters, it may compromise the goal of obtaining an overall broad picture of the field contributions. First, some of the clusters identified are very small, and had to be disregarded. Second, the number of papers covered decreases considerably, increasing the risk of missing relevant papers.

The temporal evolution of the topics associated with the clusters in Fig. 6 is shown in Fig. 7. One observes tremendous activity in the field in recent years, with most papers published after 2015, according to Fig. 7a and b, a result very similar to that observed in Fig. 5. The large predominance of Clusters "A" and "C" is also apparent in Fig. 7a. The overall increase with time in the number of papers in the clusters is common to most clusters, as indicated by the almost stable relative distributions in Fig. 7c and d.

3.4. Insights into the design of dressing materials for wound healing

The approach we present here provides an overview of a broad field but does not readily permit a detailed or critical analysis of key issues. For example, drawing conclusions related to the design of dressing materials would be interesting, but this is not feasible given the nature of the results obtained. Nevertheless, there are various ways to exploit the information generated in our landscape analysis, particularly by combining our approach with large language model (LLM) tools. This will be further elaborated upon in the outlook section of the Conclusion. To illustrate one such possibility, we conducted an exercise to gain insights into the design of dressing materials. The procedure was as follows: we used the information on the clusters listed in Tables 4 and 6 as input to three LLM chat models— OpenAI model GPT-4-turbo, Microsoft's CoPilot in Windows 11 and Google's Gemini 2.0 Flash. In the

Table 6
Titles of the clusters identified in the *network_v5-SciBERT_FOCUS* shown in Fig. 6, as suggested by model *GPT 4o-mini*.

Cluster ID	Cluster Title
A	Development and characterization of antibacterial chitosan-based hydrogels for enhanced biocompatibility in wound dressing applications
C	Advances in tissue engineering: biomaterials and therapeutic strategies for enhanced regeneration of chronic wounds
I	Enhancing dermal regeneration: assessing the role of cultured keratinocytes and grafting techniques in burn wound healing
L	Optimizing burn wound management: an analysis of dressing thickness, burn depth, and the role of silver in healing outcomes
M	Effects of low-level laser therapy (lllt) at 1359.41 nm on wound healing in irradiated rats: a photobiomodulation study
X	Antimicrobial resistance and infection patterns in burn wound infections: a focus on *pseudomonas aeruginosa* and *staphylococcus aureus* in burn patients
{36}	Metabolic response and nutritional intervention in severely burned patients: the role of anabolic hormones and catabolism
{73}	Holistic assessment and effective management of wound exudate: addressing types, odour, and patient impact for improved healing outcomes
{382}	Enhancing accurate segmentation and diagnosis of burn wounds through advanced image processing techniques
{2673}	Evaluating exudate collection methods: accurate measurement and results from pressure ulcer management therapies

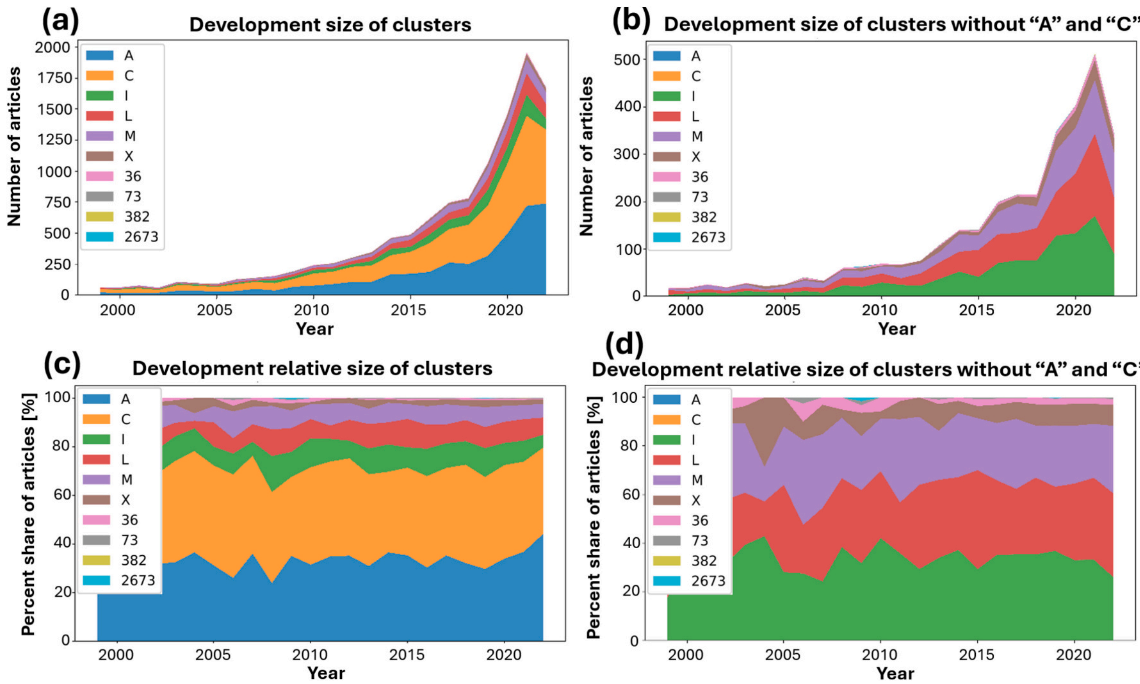

Fig. 7. Temporal evolution of the size (number of papers) of the 10 clusters in *network_v5-SciBERT_FOCUS* from 1999 to 2022. (a) Evolution of all clusters. (b) Same information after removing predominant Clusters "A" and "C". (c) Relative distribution of papers in each cluster. (d) Relative distribution without clusters "A" and "C".

initial prompts, we asked the models to provide a 400-word summary on dressing materials based on the cluster titles listed in Tables 4 and 6, considering their order of importance in terms of cluster sizes. In a second step, we instructed the models to consider their previous responses to generate an 800-word summary, with a specific focus on the design of dressing materials. We then compared the outputs of the three models and extracted the most relevant information to produce our own analysis of material design, which follows.

Based on the summaries generated by the three LLM models, we infer that designing dressing materials for chronic wounds is a multifaceted challenge that requires an understanding of the complex healing process and the interplay of various factors that can either promote or hinder recovery. Analyzing prevalent research topics reveals key design considerations, ranging from the biomaterial itself to the overall wound management strategy. The following key issues were identified.

3.4.1. Biomaterial selection for wound dressings

The most prevalent materials are antibacterial chitosan-based hydrogels, designed with a focus on several key aspects: biocompatibility, ensuring the material does not trigger an adverse bodily reaction; and drug delivery capabilities, enabling the incorporation and controlled release of therapeutic agents. The crosslinking density of chitosan, the incorporation of other polymers, and the method of drug loading are important design parameters influencing these properties. Additionally, the incorporation of bioactive agents, such as growth factors and antibiotics, enhances the therapeutic potential of hydrogels by providing sustained release to promote healing and prevent infections. Alongside chitosan-based hydrogels, the integration of silver nanoparticles into dressing materials has gained significant attention. Silver nanoparticles have potent antimicrobial properties, making them ideal for burn wound management. These dressings are designed by embedding silver nanoparticles within various carrier materials — such as hydrocolloids, foams, or gauze — to create a composite dressing that combats infections while maintaining a moist healing environment. However, the potential toxicity of silver nanoparticles necessitates careful control of their concentration and release kinetics to ensure patient safety. Another crucial aspect of dressing material selection is maintaining an effective moisture balance. Chronic wounds, such as diabetic ulcers or pressure sores, require hydrocolloid, foam, or superabsorbent dressings to sustain an optimal healing environment. Superabsorbent dressings, designed with crosslinked polymer networks, manage exudate while preventing maceration — a common challenge in chronic wound care.

3.4.2. Antimicrobial strategies in dressing design

An important design requirement is addressing the antimicrobial resistance of bacterial pathogens. This challenge has driven the development of advanced dressings capable of targeting and neutralizing resistant strains, such as *Pseudomonas aeruginosa* and *Staphylococcus aureus*, which are commonly associated with burn wound infections. These dressings often incorporate multiple antimicrobial agents or employ novel materials that disrupt bacterial biofilms, thereby enhancing their efficacy against resistant pathogens. The design must balance effective antimicrobial action with minimizing the risk of systemic toxicity or local irritation. When silver nanoparticles are used, for instance, optimizing their distribution within the dressing matrix and incorporating stabilizing agents may be necessary to regulate silver ion release. Understanding the prevalence and antimicrobial resistance of bacterial pathogens is essential for designing dressings that combat these common and often drug-resistant infections. This knowledge guides the selection of suitable antimicrobial agents and the development of delivery systems capable of overcoming bacterial resistance mechanisms.

3.4.3. Tissue engineering and multi-functional dressings

Tissue engineering approaches offer various possibilities for designing wound dressings that enhance dermal regeneration. Cultured keratinocytes and grafting techniques are employed to develop skin substitutes that can be integrated into wound dressings, providing a scaffold for cell growth and tissue repair. These engineered biomaterials mimic the extracellular matrix, promoting cell adhesion, proliferation, and differentiation, thereby accelerating the healing process. The design of these biomaterials requires careful consideration of factors such as biocompatibility, biodegradability, and mechanical properties. The scaffold must provide structural support for cells while also facilitating adhesion, proliferation, and differentiation.

Also relevant are multi-layered architectures, with each layer serving a specific function. For instance, an ideal burn wound dressing might consist of: a moisture-retaining hydrogel layer to keep the wound hydrated; an antimicrobial-infused middle layer, incorporating agents such as silver nanoparticles or iodine; a breathable outer layer that allows oxygen exchange while protecting against contamination. These multifunctional dressings are designed not only to promote healing but also to reduce the need for frequent dressing changes, minimizing patient discomfort and healthcare costs. Wound dressings can also be considered "smart" when integrated with biosensors, drug-release mechanisms, and responsive polymers. Such dressings can monitor infection markers, pH levels, and exudate composition, providing real-time data for clinicians. Additionally, stimuli-responsive dressings enable controlled drug release based on wound conditions. For example, pH-sensitive hydrogels can release antibiotics only in an infected wound environment, reducing the risk of antibiotic resistance. Similarly, thermo-responsive polymers can have their properties modified in response to temperature changes, enhancing drug diffusion and tissue integration.

3.4.4. Advanced imaging and wound monitoring technologies

An essential aspect of dressing design is ensuring that burn depth, exudate levels, and healing progression are monitored accurately. This can be achieved using noninvasive technologies such as laser Doppler imaging and infrared thermography. While these technologies are not directly part of dressing design, they may guide treatment strategies and assessing wound healing progress. In particular, when combined with machine learning and image analysis, these tools can determine wound boundaries and burn depth. Additionally, by providing real-time feedback, they enhance clinical decision-making and help optimize dressing design. They are also valuable for telemedicine applications, enabling clinicians to monitor wounds remotely and adjust treatments as needed.

3.4.5. Perspectives in dressing material design

The future of chronic wound dressings lies in personalized, adaptive, and regenerative biomaterials. Advances in 3D printing and biofabrication techniques now enable the customization of wound dressings tailored to individual patient needs. Additionally, electrospun nanofiber dressings are gaining attention for their ability to mimic the extracellular matrix, providing an optimal scaffold for cell attachment and tissue regeneration. These dressings are particularly beneficial for deep wounds and burns, where conventional materials often fail to promote adequate healing. Moreover, early excision and grafting strategies in burn care are being refined through bioprinted skin grafts, which integrate patient-derived cells to create personalized wound coverings. This approach reduces the risk of rejection and enhances long-term tissue integration.

The above summary was created using only a very small fraction of the information available from our network analysis. It serves merely to illustrate the possibility of a more refined analysis. Such refined analyses are possible, for instance, by identifying papers that represent the most central nodes in the networks and carefully analyzing them and their connections, with or without further assistance of LLM models. Additionally, the network topology itself could be used as input to LLM models to generate a structured review of the clusters and subclusters. Nevertheless, even using only the cluster titles provided a meaningful summary — though admittedly superficial, which is typical of current LLM models. We believe the reason a reasonable summary could be obtained is that the cluster titles provided the LLM models sufficient contextual information for them to build their texts.

3.5. Analysis of regions, institutions and journals

We also identified the locations, institutions and journals of the papers in the 10 most relevant clusters in the network *network_v5–SciBERT_FOCUS* in Fig. 6, which gives an overview of the topics most associated with dressing for chronic wounds. We considered the first affiliation of the paper authors, as given in the *OpenAlex* database, to identify the most represented regions and research institutions. The map in Fig. 8 shows the geographic location of the institutions appearing in the clusters selected as related to 'chronic wound'. The map also shows the (undirected) paper citation links indicating interactions. One notices a predominance of authors affiliated with institutions located in the Northern Hemisphere; indeed, Table S2 in the Supporting Information shows that the top 10 institutions identified are from the USA or China.

Given the extensive publication landscape, it may be also interesting to identify which journals are most often associated with contributions in the topic. The 10 journals most frequent in the *network_v5–SciBERT* are shown in Table 7. In the table, we also provide the paper counts for these journals in the initial corpus (whole database) and in the networks (*network_v5–BASIC* and *network_v5–SciBERT*), as well as the number of articles from these journals indexed in the SCOPUS database over the last three years. Table S3 provides some citation metrics, obtained from the *Web of Science* (*WoS*) database.

4. Conclusions

The first question we aimed to address was related to the size of the topic, specifically the number of journal papers related to dressings for chronic wound healing, which is the focus of the SWORD European project. From our various experiments with several networks as summarized in Fig. S6 and Table S4 in the Supporting Information, we found that clusters of papers relevant to this topic could be identified within networks through a focused analysis incorporating human expertise. In particular, most clusters in the networks generated using variations of the method from [11], incorporating expert provided keywords, iterative cluster selection (Fig. 4), and *SciBERT* embeddings for similarity assessment (Fig. 6), can be readily associated with dressings for chronic wound healing. Thus, we hypothesize that the topic encompasses approximately 12,000 to 20,000 papers. While this is a rough estimate, it provides an order-of-magnitude approximation that is likely more accurate than estimates based solely on direct literature searches. For instance, a query using 'chronic' and 'wound' yielded 39,695 papers on *network_v5-SciBERT_chronic_and_wound*, and 24,019 papers in *network_v5-BASIC_chronic_and_wound* many of which were irrelevant to our topic, while others were overlooked. In both networks, the temporal trend in the number of papers indicates the relative novelty of the topic, with most publications appearing after 2015.

Another important contribution from this work is to provide the overall scenario of the topics related to dressing for chronic wounds, which is better captured visualizing the 3D network models, as various aspects can only be inspected interacting with the models in the *Helios-web* platform. In terms of strategies to obtain a field landscape, input from a human expert proved useful in identifying clusters relevant to the topic of interest. Using a citation network, as in the adapted method from [11], seemed to limit the number of papers considered relevant. The strategy of employing similarity-enhanced networks based on embeddings obtained from large language models may contribute to obtaining a more precise landscape, while still preserving cluster relevance in terms of dressings used in chronic wound healing. However, this strategy yielded some very small clusters, which is undesirable, indicating a need for further work to address this limitation.

Some significant limitations in our approach should be acknowledged. First, generating a landscape focused on dressings for chronic wound healing required human expertise, which is costly. The feasibility of identifying relevant clusters in a fully automated manner, preserving the same quality, remains open to verification. For instance, one could

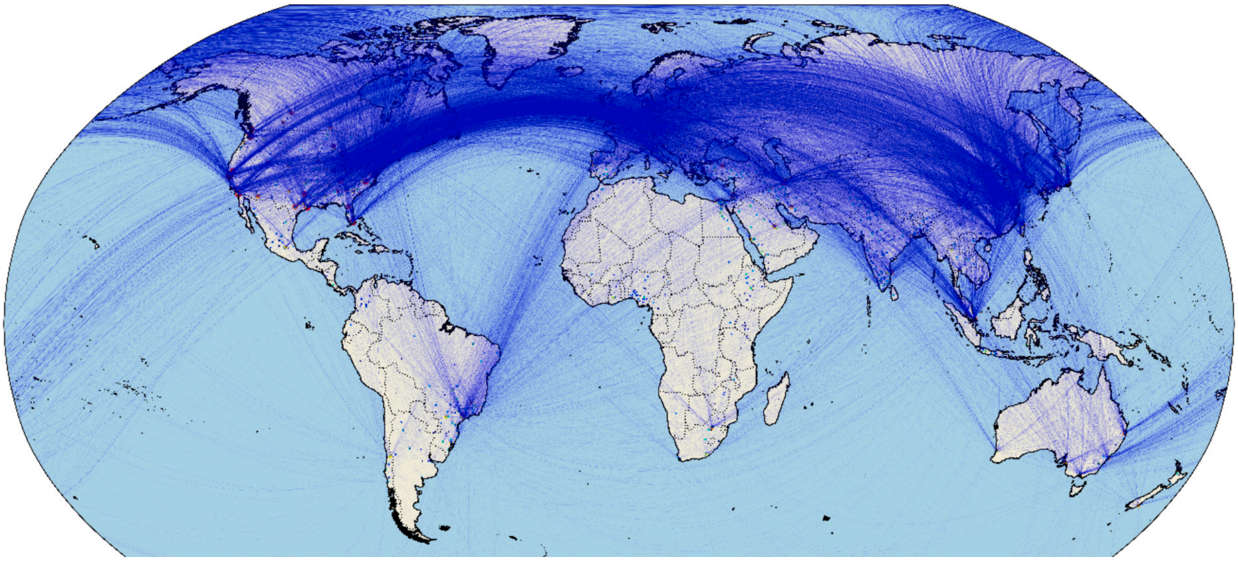

Fig. 8. Location of author affiliations and citations of papers included in the *network_v5 – SciBERT_FOCUS*.

Table 7
The 10 most prominent journals in number of papers for the different types of search and networks. The table informs, for each journal, the number of articles in the initial corpus and in the *network_v5_ BASIC* and in the *network_v5 – SciBERT*, as well as the number of articles published over the last 3 years (source: https://www.scimagojr.com/).

Journal	No. of articles			
	Whole database	*network_v5 – BASIC*	*network_v5 - SciBERT*	Total (3y) (Scimago)
International Journal of Biological Macromolecules	885	741	670	9221
Burns	1731	1024	612	833
Carbohydrate Polymers	574	494	472	4103
Materials Science and Engineering: C	493	411	362	3420
ACS Applied Materials & Interfaces	440	371	328	17,398
Wound Repair and Regeneration	2037	1403	292	273
Polymers	391	300	270	9605
Biomaterials	583	482	266	1758
International Journal of Molecular Sciences	1028	590	263	29,804
Elsevier eBooks	1287	325	259	NaN

identify key terms departing from a more focused search in *OpenAlex*, ensuring that all retrieved papers are relevant to the topic, and then use these terms to build focused networks from papers retrieved with more broadly generated queries. Furthermore, the approach introduced does not provide a detailed analysis of the topical contents. For example, the experiments indicated that chitosan-based hydrogels are among the most employed materials for dressings, but no further inferences can be made from the information given. We could not determine the common materials used for dressings, which could be attained with other approaches, such as in the study aimed at inferring specific information through mining the literature [57].

The methodology in this study was motivated by our earlier work [11], developed before the emergence of large-language model (LLM)-based tools. Our approach could be integrated with such tools for various applications, including trend identification, evidence-based decision-making, automated literature reviews, and global research comparisons. For wound healing, tracking the evolution of key topics helps detect emerging materials and technologies. For example, in the section on dressing material design, we highlighted the growing interest in smart dressings, which incorporate biosensors for real-time wound monitoring and AI-driven wound management. Additionally, this approach enables more detailed comparisons, such as evaluating the antibacterial efficacy of different dressing materials, including hydrogels, hydrocolloids, alginates, and silver nanoparticle-based dressings. Moreover, citation analysis provides a quantitative measure of research impact, helping scientists identify the most influential materials and studies in wound healing. This methodology also facilitates systematic reviews without extensive manual effort. By combining citation networks with NLP-generated summaries, researchers can accelerate literature reviews and stay updated in fast-evolving fields. Applicability obviously extends far beyond the specific topic of wound healing.

Beyond wound healing, but still related to biological macromolecules, this approach is applicable to pharmaceutical research, medical device development, and epidemiology. In drug discovery, network analysis and NLP can identify key compounds, study interactions, and explore therapeutic applications. In biomedical engineering, it aids in assessing medical device performance, patient outcomes, and regulatory trends, while also identifying innovation opportunities and safety gaps. Furthermore, analyzing research networks provides insights into disease spread, vaccination strategies, and public health interventions. By examining citation networks and language patterns, researchers can evaluate policy effectiveness and highlight areas for further study.

CRediT authorship contribution statement

Jaromir Klarak: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ana Caroline M. Brito:** Visualization, Validation, Software, Data curation. **Luan F. Moreira:** Software, Data curation. **Filipi N. Silva:** Visualization, Software, Data curation. **Diego R. Amancio:** Validation, Investigation. **Robert Andok:** Supervision, Resources, Project administration, Funding acquisition. **Maria Cristina F. Oliveira:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis. **Maria Bardosova:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis. **Osvaldo N. Oliveira:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Osvaldo N. Oliveira Jr. reports financial support was provided by State of Sao Paulo Research Foundation, CNPq. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by CNPq and FAPESP (2018/22214-6, 2020/14817-2) (Brazil), H2020-MSCA-RISE-2019-873123: Smart Wound Monitoring Restorative Dressings (SWORD), by the Slovak Research and Development Agency under the Contract no. APVV-23-0173, by the VEGA grant No. 2/0099/22 and by EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project ENEFS in call 09I05-03-V02.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijbiomac.2025.141565.

References

[1] Rise in higher education researchers and academic publications, Emerald Open Res. 1 (3) (2020), https://doi.org/10.1108/EOR-03-2023-0008.

[2] S. Fortunato, et al., Science of science, Science *(80)* 359 (6379) (Mar. 2018), https://doi.org/10.1126/SCIENCE.AAO0185/ASSET/297C7FEB-7421-44D7-8A2E-CC73607D9E02/ASSETS/GRAPHIC/359_AAO0185_F5.JPEG.

[3] A.C.M. Brito, M.C.F. Oliveira, O.N. Oliveira, F.N. Silva, D.R. Amancio, Network analysis and natural language processing to obtain a landscape of the scientific literature on materials applications, ACS Appl. Mater. Interfaces 15 (23) (Jun. 2023) 27437–27446, https://doi.org/10.1021/ACSAMI.3C01632.

[4] L. Liu, B.F. Jones, B. Uzzi, D. Wang, Data, measurement and empirical methods in the science of science, Nat. Hum. Behav. 2023 77 7 (7) (Jun. 2023) 1046–1058, https://doi.org/10.1038/s41562-023-01562-4.

[5] A. Zeng, et al., The science of science: from the perspective of complex systems, Phys. Rep. 714–715 (Nov. 2017) 1–73, https://doi.org/10.1016/J.PHYSREP.2017.10.001.

[6] S.H. Strogatz, Exploring complex networks, Nat. 2001 4106825 410 (6825) (Mar. 2001) 268–276, https://doi.org/10.1038/35065725.

[7] Q. Ji, D. Li, Z. Jin, Divisive algorithm based on node clustering coefficient for community detection, IEEE Access 8 (2020) 142337–142347, https://doi.org/10.1109/ACCESS.2020.3013241.

[8] F. Battiston, et al., The physics of higher-order interactions in complex systems, Nat. Phys. 2021 1710 17 (10) (Oct. 2021) 1093–1098, https://doi.org/10.1038/s41567-021-01371-4.

[9] M. Boguñá, I. Bonamassa, M. De Domenico, S. Havlin, D. Krioukov, M.Á. Serrano, Network geometry, Nat. Rev. Phys. 2021 32 3 (2) (Jan. 2021) 114–135, https://doi.org/10.1038/s42254-020-00264-4.

[10] M.E.J. Newman, The Structure and Function of Complex Networks, 2003.

[11] F.N. Silva, D.R. Amancio, M. Bardosova, L. da F. Costa, O.N. Oliveira, Using network science and text analytics to produce surveys in a scientific topic, J. Inf. Secur. 10 (2) (May 2016) 487–502, https://doi.org/10.1016/j.joi.2016.03.008.

[12] A.C.M. Brito, M.C.F. Oliveira, O.N. Oliveira, F.N. Silva, D.R. Amancio, History of chemistry of materials according to topic evolution based on network analysis and natural language processing, Chem. Mater. 36 (1) (Jan. 2024) 1–7, https://doi.org/10.1021/ACS.CHEMMATER.3C02962/ASSET/IMAGES/LARGE/CM3C02962_0006.JPEG.

[13] K.Y. Tang, C.Y. Chang, G.J. Hwang, Trends in artificial intelligence-supported e-learning: a systematic review and co-citation network analysis (1998–2019), Interact. Learn. Environ. 31 (4) (May 2023) 2134–2152, https://doi.org/10.1080/10494820.2021.1875001.

[14] "Helios-web - Filipi N. Silva." Accessed: Nov. 17, 2023. [Online]. Available: https://filipinascimento.github.io/software/heliosweb/.

[15] N.J. van Eck, L. Waltman, Software survey: VOSviewer, a computer program for bibliometric mapping, Scientometrics 84 (2) (Dec. 2010) 523–538, https://doi.org/10.1007/S11192-009-0146-3/FIGURES/7.

[16] N. Jan van Eck, L. Waltman, VOSviewer Manual, 2019.

[17] "Learn how to use Gephi." Accessed: Jan. 09, 2024. [Online]. Available: https://gephi.org/users/.

[18] Q. Guo, et al., Visualization of the relationship between macrophage and wound healing from the perspective of bibliometric analysis, Int. Wound J. (Dec. 2023), https://doi.org/10.1111/IWJ.14597.

[19] K. Tang, Z. Cai, Y. Lv, R. Liu, Q. Chen, J. Gu, Scientometric research on trend analysis of nano-based sustained drug release systems for wound healing, Pharmaceutics 15 (4) (Apr. 2023) 1168, https://doi.org/10.3390/PHARMACEUTICS15041168/S1.

[20] H. Meng, Y. Peng, P. Li, J. Su, Y. Jiang, X. Fu, Global trends in research of high-throughput sequencing technology associated with chronic wounds from 2002 to 2022: a bibliometric and visualized study, Front. Surg. 10 (Feb. 2023) 1089203, https://doi.org/10.3389/FSURG.2023.1089203/BIBTEX.

[21] J. Zhang, H. Liu, T. Che, Y. Zheng, X. Nan, Z. Wu, Nanomaterials for diabetic wound healing: visualization and bibliometric analysis from 2011 to 2021, Front. Endocrinol. (Lausanne) 14 (Jan. 2023) 1124027, https://doi.org/10.3389/FENDO.2023.1124027/BIBTEX.

[22] M.L. Zha, J.Y. Cai, H.L. Chen, A bibliometric analysis of global research production pertaining to diabetic foot ulcers in the past ten years, J. Foot Ankle Surg. 58 (2) (Mar. 2019) 253–259, https://doi.org/10.1053/J.JFAS.2018.08.052.

[23] Z. Zhou, et al., Natural polymer nanofiber dressings for effective management of chronic diabetic wounds: a comprehensive review, Int. J. Biol. Macromol. 282 (Dec. 2024) 136688, https://doi.org/10.1016/J.IJBIOMAC.2024.136688.

[24] F. Mottaghitalab, M. Farokhi, Stimulus-responsive biomacromolecule wound dressings for enhanced drug delivery in chronic wound healing: a review, Int. J. Biol. Macromol. 281 (Nov. 2024) 136496, https://doi.org/10.1016/J.IJBIOMAC.2024.136496.

[25] I.J. Das, T. Bal, pH factors in chronic wound and pH-responsive polysaccharide-based hydrogel dressings, Int. J. Biol. Macromol. 279 (Nov. 2024) 135118, https://doi.org/10.1016/J.IJBIOMAC.2024.135118.

[26] P. Amruth, P. Akshay, M. Rosemol Jacob, J.M. Joy, S. Mathew, Developmental prospects of carrageenan-based wound dressing films: unveiling techno-functional properties and freeze-drying technology for the development of absorbent films — a review, Int. J. Biol. Macromol. 276 (Sep. 2024) 133668, https://doi.org/10.1016/J.IJBIOMAC.2024.133668.

[27] A. de Oliveira, Silva Guerrero, et al., Chitosan-based films filled with nanoencapsulated essential oil: physical-chemical characterization and enhanced wound healing activity, Int. J. Biol. Macromol. 261 (Mar. 2024) 129049, https://doi.org/10.1016/J.IJBIOMAC.2023.129049.

[28] P. Wang, et al., Emerging trends in the application of hydrogel-based biomaterials for enhanced wound healing: a literature review, Int. J. Biol. Macromol. 261 (Mar. 2024) 129300, https://doi.org/10.1016/J.IJBIOMAC.2024.129300.

[29] M.N. Gupta, V.N. Uversky, Biological importance of arginine: a comprehensive review of the roles in structure, disorder, and functionality of peptides and proteins, Int. J. Biol. Macromol. 257 (Feb. 2024) 128646, https://doi.org/10.1016/J.IJBIOMAC.2023.128646.

[30] M. Sharifi, S.H. Bahrami, Review on application of herbal extracts in biomacromolecules-based nanofibers as wound dressings and skin tissue engineering, Int. J. Biol. Macromol. 277 (Oct. 2024) 133666, https://doi.org/10.1016/J.IJBIOMAC.2024.133666.

[31] L. Qiao, et al., Antibacterial conductive self-healing hydrogel wound dressing with dual dynamic bonds promotes infected wound healing, Bioact. Mater. 30 (Dec. 2023) 129–141, https://doi.org/10.1016/j.bioactmat.2023.07.015.

[32] Y. Yang, et al., Bacteria-responsive programmed self-activating antibacterial hydrogel to remodel regeneration microenvironment for infected wound healing, Natl. Sci. Rev. 11, no. 4 (Apr. 2024) nwae044, https://doi.org/10.1093/nsr/nwae044.

[33] Q. Han, et al., Injectable bioadhesive Photocrosslinkable hydrogels with sustained release of Kartogenin to promote Chondrogenic differentiation and partial-thickness cartilage defects repair, Adv. Healthc. Mater. 13 (9) (Apr. 2024) 2303255, https://doi.org/10.1002/adhm.202303255.

[34] Y. Shan, et al., Procoagulant, antibacterial and antioxidant high-strength porous hydrogel adhesives in situ formed via self-gelling hemostatic microsheets for emergency hemostasis and wound repair, Biomaterials 315 (Apr. 2025) 122936, https://doi.org/10.1016/j.biomaterials.2024.122936.

[35] X. Zhang, Y. Liang, S. Huang, B. Guo, Chitosan-based self-healing hydrogel dressing for wound healing, Adv. Colloid Interface Sci. 332 (Oct. 2024) 103267, https://doi.org/10.1016/j.cis.2024.103267.

[36] X. Che, et al., Application of chitosan-based hydrogel in promoting wound healing: a review, Polymers (Basel). 16 (3) (Feb. 2024) 344, https://doi.org/10.3390/polym16030344.

[37] D.J. McClements, Composite hydrogels assembled from food-grade biopolymers: fabrication, properties, and applications, Adv. Colloid Interface Sci. 332 (Oct. 2024) 103278, https://doi.org/10.1016/J.CIS.2024.103278.

[38] Y. Wang, Z. Wang, W. Lu, Y. Hu, Review on chitosan-based antibacterial hydrogels: preparation, mechanisms, and applications, Int. J. Biol. Macromol. 255 (Jan. 2024) 128080, https://doi.org/10.1016/j.ijbiomac.2023.128080.

[39] T. Zhou, H. Zhou, F. Wang, P. Zhang, J. Shang, L. Shi, An injectable carboxymethyl chitosan hydrogel scaffold formed via coordination bond for antibacterial and osteogenesis in osteomyelitis, Carbohydr. Polym. 324 (Jan. 2024) 121466, https://doi.org/10.1016/j.carbpol.2023.121466.

[40] A. Li, et al., Chitosan-based injectable hydrogel with multifunction for wound healing: a critical review, Carbohydr. Polym. 333 (Jun. 2024) 121952, https://doi.org/10.1016/j.carbpol.2024.121952.

[41] M. Kumar, S. Mahmood, S. Chopra, A. Bhatia, Biopolymer based nanoparticles and their therapeutic potential in wound healing – a review, Int. J. Biol. Macromol. 267 (May 2024) 131335, https://doi.org/10.1016/j.ijbiomac.2024.131335.

[42] Y. Zhu, et al., Strategies of functionalized GelMA-based bioinks for bone regeneration: recent advances and future perspectives, Bioact. Mater. 38 (Aug. 2024) 346–373, https://doi.org/10.1016/j.bioactmat.2024.04.032.
[43] Q. Jia, et al., Hydrogel loaded with peptide-containing nanocomplexes: symphonic cooperation of photothermal antimicrobial nanoparticles and prohealing peptides for the treatment of infected wounds, ACS Appl. Mater. Interfaces 16 (11) (Mar. 2024) 13422–13438, https://doi.org/10.1021/acsami.3c16061.
[44] Q. Guo, T. Yin, W. Huang, R. Nan, T. Xiang, S. Zhou, Hybrid hydrogels for immunoregulation and proangiogenesis through mild heat stimulation to accelerate whole-process diabetic wound healing, Adv. Healthc. Mater. 13 (18) (Jul. 2024) 2304536, https://doi.org/10.1002/adhm.202304536.
[45] W. Guo, et al., Self-adhesive and self-healing hydrogel dressings based on quaternary ammonium chitosan and host-guest interacted silk fibroin, Colloids Surf. A Physicochem. Eng. Asp. 684 (Mar. 2024) 133145, https://doi.org/10.1016/j.colsurfa.2024.133145.
[46] B.M. Kyaw, K. Järbrink, L. Martinengo, J. Car, K. Harding, A. Schmidtchen, Need for improved definition of 'chronic wounds' in clinical studies, Acta Derm. Venereol. 98 (1) (2018) 157–158, https://doi.org/10.2340/00015555-2786.
[47] K. Harding, 'Woundology'—an emerging clinical specialty, Int. Wound J. 5 (5) (Dec. 2008) 597, https://doi.org/10.1111/J.1742-481X.2008.00569.X.
[48] M. Costagliola, B. Atiyeh, Vulnerology: a new term to describe the discipline of wound care, Int. Wound J. 11 (3) (2014) 269–273, https://doi.org/10.1111/J.1742-481X.2012.01086.X.
[49] H. Li, B. Cheng, C. Zhang, Editorial: wound repair: establishment and development of a new discipline in China, Front. Surg. 10 (May 2023) 1207709, https://doi.org/10.3389/FSURG.2023.1207709/BIBTEX.
[50] "OpenAlex snapshot - OpenAlex API documentation." Accessed: Apr. 26, 2023. [Online]. Available: https://docs.openalex.org/download-all-data/openalex-snapshot.
[51] "Filter works - OpenAlex API documentation." Accessed: Nov. 20, 2023. [Online]. Available: https://docs.openalex.org/api-entities/works/filter-works.
[52] P. Sharma, Y. Li, Self-Supervised Contextual Keyword and Keyphrase Retrieval with Self-Labelling, Aug. 2019, https://doi.org/10.20944/PREPRINTS201908.0073.V1.
[53] "MaartenGr/KeyBERT: Minimal keyword extraction with BERT." Accessed: Nov. 21, 2023. [Online]. Available: https://github.com/MaartenGr/KeyBERT.
[54] M. Rosvall, D. Axelsson, C.T. Bergstrom, The map equation, Eur. Phys. J. Spec. Top. 178 (1) (Jan. 2009) 13–23, https://doi.org/10.1140/epjst/e2010-01179-1.
[55] I. Beltagy, K. Lo, A. Cohan, SCIBERT: A pretrained language model for scientific text, in: EMNLP-IJCNLP 2019–2019 Conf. Empir. Methods Nat. Lang. Process. 9th Int. Jt. Conf. Nat. Lang. Process. Proc. Conf, 2019, pp. 3615–3620, https://doi.org/10.18653/v1/d19-1371.
[56] F.N. Silva, F.A. Rodrigues, O.N. Oliveira, L. Da, F. Costa, Quantifying the interdisciplinarity of scientific journals and fields, J. Informetr. 7 (2013) 469–477, https://doi.org/10.1016/j.joi.2013.01.007.
[57] A.J. Paula, O.P. Ferreira, A.G. Souza Filho, F.N. Filho, C.E. Andrade, A.F. Faria, Machine learning and natural language processing enable a data-oriented experimental design approach for producing biochar and hydrochar from biomass, Chem. Mater. 34 (3) (Feb. 2022) 979–990, https://doi.org/10.1021/ACS.CHEMMATER.1C02961/SUPPL_FILE/CM1C02961_SI_001.PDF.