

A text mining and network analysis of topics and trends in major nursing research journals

Beratiye Oner¹  | Orhan Hakli² | Ferhat D. Zengul^{3,4,5} 

¹Department of Nursing, Faculty of Health Sciences, Lokman Hekim University, Ankara, Turkey

²School of Nursing and Health Sciences, Manhattanville College, Purchase, New York, USA

³Department of Health Services Administration, The University of Alabama at Birmingham, Birmingham, Alabama, USA

⁴Informatics Institute, The University of Alabama at Birmingham, Birmingham, Alabama, USA

⁵Electrical & Computer Engineering, The Center for Integrated Systems, The University of Alabama at Birmingham, Birmingham, Alabama, USA

Correspondence

Beratiye Oner, Department of Nursing, Faculty of Health Sciences, Lokman Hekim University, Ankara, Turkey.

Email: beratiye.oner@lokmanhekim.edu.tr

Ferhat D. Zengul, Department of Health Services Administration, The University of Alabama at Birmingham, Birmingham, Alabama, USA.

Email: ferhat@uab.edu

Abstract

Aim: This study is set to determine the main topics of the nursing field and to show the changing perspectives over time by analysing the abstracts of several major nursing research journals using text mining methodology.

Design: Text mining and network analysis.

Methods: Text analysis combines automatic and manual operations to identify patterns in unstructured data. Detailed searches covering 1998–2021 were conducted in PubMed archives to collect articles from six nursing journals: *Journal of Advanced Nursing*, *International Journal of Nursing Studies*, *Western Journal of Nursing Research*, *Nursing Research*, *Journal of Nursing Scholarship* and *Research in Nursing and Health*. This study uses a four-phase text mining and network approach, gathering text data and cleaning, preprocessing, text analysis and advanced analyses. Analyses and data visualization were performed using Endnote, JMP, Microsoft Excel, Tableau and VOSviewer versions. From six journals, 17,581 references in PubMed were combined into one EndNote file. Due to missing abstract information, 2496 references were excluded from the study. The remaining references ($n=15,085$) were used for the text mining analyses.

Results: Eighteen subjects were determined into two main groups; research method topics and nursing research topics. The most striking topics are qualitative research, concept analysis, advanced practice in the downtrend, and literature search, statistical analysis, randomized control trials, quantitative research, nurse practice environment, risk assessment and nursing science. According to the network analysis results, nursing satisfaction and burnout and nursing practice environment are highly correlated and represent 10% of the total corpus. This study contributes in various ways to the field of nursing research enhanced by text mining. The study findings shed light on researchers becoming more aware of the latest research status, sub-fields and trends over the years, identifying gaps and planning future research agendas. No patient or public contribution.

KEY WORDS

network analysis, nursing, research, text mining, topics, trends

1 | INTRODUCTION

In recent years, there has been a growing interest in analysing data to understand and predict the trends of healthcare practices in nursing (Rufang et al., 2019). The main reason for this interest lies in the need to position the profession for the challenges of the ever-dynamic modern world. The central issue in today's fast-paced world is the difficulty of forecasting potential problems in time and determining how to solve them before they turn into crises. However, due to nursing's interprofessional nature and significant scope of practice, these problems could have a wide range and be hard to analyse. Therefore, knowledge of the most researched topics and creating topic areas based on their similarities could help nurses in many ways, such as realizing the gap in research topics, seeing trends and predicting patterns. In addition, nursing professionals could use this knowledge for direct patient care, staffing and finance. This knowledge could help both the current nursing practice and the future of nursing as nursing schools' curricula could be revised.

Theory and clinical practice are inseparable parts of the nursing profession (Roy, 2018), and the needs of the field usually impact the number of studies published in a particular area. However, more work is needed to determine these areas and their trends methodologically. Text mining and natural language processing provide tools to interpret large volumes of textual data and establish a more holistic view of the nursing domain. It is relatively easy and very beneficial to turn a large set of unstructured data that is growing faster than any manual system can catch up with into meaningful, well-organized information (Delen & Crossland, 2008). However, although many text mining studies can be found in the literature, to our knowledge, they focus either only on specific nursing problems or on topics and trends in other disciplines, such as healthcare management, health services research, health policy, health economics, nephrology, cancer and COVID-19 (Lee et al., 2018; Leurs et al., 2022; Won et al., 2021; Zengul et al., 2020, 2021, 2022).

Text mining methods can be divided into three main categories: topic analyses, semantic analyses and network analyses. Topic analyses are primarily aimed at determining which subjects or themes stand out within a collection of documents. These analyses are used to identify collections of words or phrases grouped around a specific topic or theme. The most common topic modelling methods are Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA) and Probabilistic Latent Semantic Analysis (pLSA) (Blei et al., 2003; Deerwester et al., 1990; Hofmann, 1999).

Semantic analyses focus on studying the meanings of words or phrases in texts and how these meanings come together. Semantic analyses are used to define subjective tones, emotional charges, or relationships between specific concepts in texts. Semantic models rely on word embedding methods such as Word2Vec, FastText, and BERT (Bojanowski et al., 2017; Devlin et al., 2018; Mikolov et al., 2013). Network analyses are used to visualize and analyse relationships between words or phrases within a text. Network analyses help understand which words or phrases appear together in a text

and which concepts are central or peripheral. Text Network Analysis (TNA) is one of the primary methods in this category. TNA is a bridge between textual analysis and network theory (Paranyushkin, 2011).

The examples of text mining studies focusing on specific nursing problems tended to use predominantly nursing notes and had limited scope. For example, Leurs et al. (2022) used text mining strategies to determine the risk factors leading to falls in older people (Leurs et al., 2022). In the study, the researchers investigated the nurses' free text notes and found that certain words used frequently in a patient's record, especially in the last 72 h, indicate that it is likely for this patient to experience a fall. Although this is an important finding to predict and perhaps avoid falls, the study's scope appeared to be narrow because they only focused on in-patient elderly clients and falls. Similarly, Bjarnadottir and Lucero (2018) were able to determine the risk factors for falls of hospitalized patients by using text mining strategies with registered nurses' notes (Bjarnadottir & Lucero, 2018). Another text mining study was performed by Hyun and Cooper (2020), who analysed intensive care nurses' free text notes to fill the knowledge gap about intensive care unit patients' clinical stories. This study did produce meaningful results, but again, it was limited to the intensive care unit setting. Kushima et al. (2011) similarly used text mining strategies to analyse nursing notes of past patients at a hospital in Japan. The researchers found this technique helpful to reach their goal of visualizing information to detect disease and classify it from electronic medical record documentation (Kushima et al., 2011). In another study, Lee et al. (2018) also used text mining strategies. The aim of their study was to examine the trends in oncology research and investigate priorities in Japanese oncology nursing to reveal challenges in oncology nursing (Lee et al., 2018).

In some studies, the researchers aimed to extract patterns from published research articles; however, such studies tended to have very narrow focus. For example, Won et al. (2021) used text mining to predict trends in nursing. However, they only investigated trends related to research on infections rather than the profession as a whole. In another study using data mining, the researchers explored factors associated with pressure ulcers (Raju et al., 2015). For example, Ozaydin et al. (2017) used text mining to try to determine the major subject areas and their trends and summarize the evolution of mobile health. Similarly, Hao et al. (2018) published a study analysing medical studies published between 2008 and 2017 to examine and summarize the current advances in medical research.

As demonstrated in the literature review, no text mining study focused on the evolution of nursing research or the nursing field as a whole. In nursing, studies that used text mining and natural language processing focused on nursing and clinical notes or a specific nursing topic. Therefore, it would be of interest to learn what nursing researchers have been working on and how these topics have changed over the years as a whole instead of focusing on specific problems. Such a methodological approach would help the stakeholders shape the future of the nursing profession, identify the gaps in knowledge in research and help fellow researchers in their future studies. Hence, our primary objective in this paper was

to identify the main topic areas of nursing research and their trends between 1998 and 2021.

2 | METHODS

2.1 | Design

In this study, we conducted LSA due to its ability to uncover the underlying structure and relationships within large text corpora. LSA offers several advantages over traditional keyword frequency and co-occurrence analyses. LSA allows for the distillation of essential topics by reducing the data dimensionality through singular value decomposition (SVD). The dimension reduction process results in a more focused and meaningful extraction of topics. LSA also can capture implicit relationships and semantic structures in the text, offering a more profound understanding than mere keyword occurrences. By focusing on latent structures, LSA minimizes the impact of noise and outliers in the data (Deerwester et al., 1990). In addition to LSA, we employed a network analysis based on topic word co-occurrence complementing the LSA findings. This network visualizes the strength and patterns of relationships between statistically significant topics, providing readers with an intuitive grasp of the landscape of nursing research topics and their interrelationships.

We used a four-stage text mining approach; (1) gathering text data and cleaning, (2) text preprocessing, (3) text analysis and (4) advanced analyses (Table 1) (see Appendix S1).

2.2 | Gathering text data and cleaning

In the first stage, the top six general nursing journals were identified using Scientific Journal Rankings and a publication focusing on an evidence-based list of journals. All nursing journals in the Q1 and Q2 categories are listed based on Scientific Journal Rankings, excluding clinical practice journals and specialty journals in nursing. Considering the H indexes and Scientific Journal Rankings scores, six journals were chosen by two nursing experts (26 years of career practice and 14 years of an academic career; a 12-year career with the university hospital and 10 years of an academic career). Detailed searches covering 1998 through 2021 were conducted in PubMed archives to collect articles from six nursing journals: *Journal of Advanced Nursing*, *International Journal of Nursing Studies*, *Western Journal of Nursing Research*, *Nursing Research*, *Journal of Nursing Scholarship*, and *Research in Nursing and Health*.

We combined 17,581 references (1998–2021) from six journals from PubMed into an EndNote file. Due to missing abstracts, 2496 references were excluded from the study. The remaining article abstracts ($n=15,085$) were used for the text mining analyses. This study covered six general nursing journals and included all types of published work (i.e. empirical studies, systematic reviews, meta-analyses and randomized control trials) except editorials, prefaces and references without abstracts.

2.3 | Text preprocessing

The procedure of cleaning and preparing textual data for text analyses is called text preprocessing (Haddi et al., 2013). Text preprocessing consists of lowercase/uppercase conversion; removing punctuation, numbers or unwanted characters; tokenization; stemming; stop word removal; recoding or renaming (Nayak et al., 2016) (see Appendix S1 for the definitions of Natural Language Processing terminology and their applications within this study). As a result of the text preprocessing, 4459 relevant and meaningful terms were identified and used in the topic analysis. A document-term matrix was created using the final term list. We normalized term usage by term frequency-inverse document frequency (Appendix S1).

2.4 | Text analysis

Text mining employs a variety of analyses. Text analyses can be used for clustering or classification (Gupta & Lehal, 2009). Our data were not labelled data. Thus, we conducted latent semantic analysis, one of the clustering methods.

Latent semantic analysis is a text mining method to compute a partial singular vector decomposition of the document-term matrix. Singular vector decomposition decomposes the document-term matrix into a lower-dimensional representation that captures the underlying relationships between the terms and documents. The document-term matrix is converted into a document-topic matrix (U), singular values matrix (Σ) and topic-term matrix (V) through singular vector decomposition. Based on the Σ matrix, we determine the number of singular values (k) to reduce the dimensions (Appendix S1). The singular value also represents the number of topics (Evangelopoulos et al., 2012; Hofmann, 2001; Landauer et al., 2004).

Topic analysis is a rotated singular vector decomposition using varimax rotation (JMP® 16). The varimax rotation maximizes the variance of the squared loadings for each topic while minimizing the variance across topics (Kaiser, 1958). This helps to find the essential terms in each topic. A rotated singular vector decomposition provides three matrices parallel to the truncated singular vector decomposition by the (k) value (Abdi, 2003; Chang et al., 2019; Hyun & Cooper, 2020).

Latent semantic analysis allows for the creation of as many topics as documents. However, thousands of topics are not easily interpreted, and examining them takes time. Dimension reduction on the topics can reveal the leading topics. Focusing on the leading topics can increase model interpretability (Cunningham, 2008). Thus, first, we conducted a latent semantic analysis based on 100 topics. Eigenvalues for 100 dimensions varied between 1.62 and 10.32. The most common methods to find the optimal (k) are elbow method and coherence scores. Elbow method tries to detect 'elbow' shape in a scree plot, which is the point where adding more topics does not give much more explained variance. A scree plot is a scatter plot that shows the relationship between

TABLE 1 Four-step text mining approach.

Stages	Steps		
1. Gathering text data and cleaning	17,581 references were gathered for six selected nursing journals: JAN: 7473 IJNS: 3583 WJNR: 1896 NR: 1508 JNS: 1473 RINAH: 1648	2496 references were excluded: Editorials, prefaces, and references without abstracts	15,085 references were included: JAN: 6705 IJNS: 3124 WJNR: 1529 NR: 1307 JNS: 1269 RINAH: 1151
2. Text preprocessing	Tokenization, stemming, recoding and term curations: Removed punctuations and numbers using Regex. Stop words were removed	Term list: 4459 relevant and meaningful terms (tokens) were identified	Creating a document-term matrix: The document-term matrix was weighted by term frequency-inverse document frequency
3. Text analysis	Dimension reduction: Extracted 100 dimensions through singular vector decomposition (latent semantic analysis)	Rotated singular vector decomposition: Performed topic analysis	Determining topics: 18 topics were identified based on threshold values ($k=18$)
4. Advanced analyses	Topic labelling: Topic-term lists Word clouds Documents' topics Topic strengths	Trend analysis: Uptrending, downtrending, and stable topics were plotted	Network analysis: Mapped co-occurrence topics and terms

Note: Adapted from Miner et al. (2012).

Abbreviations: IJNS, International Journal of Nursing Studies; JAN, Journal of Advanced Nursing; JNS, Journal of Nursing Scholarship; NR, Nursing Research; RINAH, Research in Nursing and Health; WJNR, Western Journal of Nursing Research.

the number of dimensions or topics and their eigenvalues or singular values. The optimal (k) is the elbow point(s) on the scree plot (Kodinariya & Makwana, 2013; Liu & Deng, 2020). On the other hand, coherence scores measure the semantic similarity of the high-scoring words within each topic. A better coherence score indicates that the words in the topic are more semantically similar to each other. The common coherence score methods for topic modelling include the C_v measure, U_mass measure, C_uci and C_umn measures based on pointwise mutual information, C_npmi measure, C_w2v measure leveraging word embeddings and the C_pmi measure (Röder et al., 2015). Unsupervised models, like topic modelling algorithms, cluster data based on inherent structures without any predefined labels. Thus, determining the quality, coherence or relevance of the results often requires human interpretation. Griffiths and Steyvers (2004) emphasized the role of human judgement in evaluating the quality and interpretability of topics. They suggested that while various statistical measures can provide guidance on the number of topics, the final decision often benefits from human expertise to ensure the topics are coherent, interpretable and aligned with the objectives of the analysis (Griffiths & Steyvers, 2004). Due to the reasons explained above, we evaluated the results obtained using both the elbow method and coherence scores to determine the optimal number of topics. We first conducted the elbow method. We observed that the optimal (k) can be between 15 and 20 on the scree plot (see Appendix S2). We then calculated coherence scores for 20 topics using U_mass measure. Even though the coherence scores indicate only the first two topics ($U_{mass} = -1722$) are optimal,

we observed first 18 topics (eigenvalue threshold = 3.92) have great potential to provide distinguished topics (see Appendix S3). Consequently, we identified 18 topics that are more coherent. In Appendix S4, we present tables detailing topic terms, accompanied by their respective eigenvalues and coherences. These term loadings, derived using the rotated SVD method, reflect the significance of each term to its corresponding topic. A higher loading indicates a greater contribution and vice versa.

2.5 | Advanced analyses

Advanced analyses include topic labelling, trend analysis and network analysis. Latent semantic analysis does not provide the topic labels but produces topic terms, documents' topic membership and topic strengths. Instead, topic labels can be created based on expert opinion. Thus, we prepared reports that included topic-term lists, word clouds and the top three representative references for each topic. We then sent the reports to 11 independent academic and clinical experts in the nursing field. The authors also separately reviewed the reports and finalized topic labelling with consensus.

Trend analysis helps to examine the topic changes throughout a period. We plotted the trends based on topic proportions. The topic proportions were calculated by $\frac{\text{Number of the documents labeled for } x \text{ topic}}{\text{Number of total references in the year}}$. We marked trends as uptrends, stable and downtrends.

Network analysis revealed the relationship between the words appearing in the text using maps, and we interpreted the

phenomenon through these networks. Network analysis reveals relationships between objects that help to understand a situation or phenomenon more clearly (Shi et al., 2017). We used the topic-term lists as network data. The network map was created based on topic-term co-occurrences. We also conducted a cluster analysis on the network map (Waltman et al., 2010). The association strength method was used to normalize the strength of topic-term co-occurrences (Eck & Waltman, 2009). Clusters were limited to a minimum of two topic terms.

2.6 | Data analysis tools

As EndNote version 20 and Microsoft Excel for Mac version 16.68 were used for data collection and primary data cleaning, natural language processing methods and text mining analyses were conducted in JMP version 16 Pro. Word cloud images, tables and figures were created using Tableau version 2021.1 and Microsoft Excel. Trend analyses were conducted through JMP 16 Pro. Network analysis was performed using VOSviewer version 1.6.18.

3 | RESULTS

3.1 | Topics

The topics were divided into two groups: research method topics and nursing research topics. The research method topics were as follows: Topic 1: literature search, Topic 2: statistical analysis, Topic 3: qualitative research, Topic 4: quantitative research, Topic 5: concept analysis and Topic 8: randomized control trials. The nursing research topics were as follows: Topic 6: nursing satisfaction and burnout, Topic 7: advanced practice, Topic 9: nurse practice environment, Topic 10: risk assessment, Topic 11: neonatal care, Topic 12: chronic illness management, Topic 13: nursing science, Topic 14: nutrition and health, Topic 15: infection control, Topic 16: maternal nursing care, Topic 17: sleep quality among nurses and Topic 18: geriatric care.

The ranking of topics from 1 to 18 in [Table 2](#) represents the percentage of corpus variation explained by each topic. Qualitative research (Topic 3), concept analysis (Topic 5) and advanced practice (Topic 7) were the most frequent topics. Quantitative research (Topic 4), sleep quality among nurses (Topic 17) and neonatal care (Topic 11) were the least frequent topics.

The *Journal of Advanced Nursing* has a noticeable share in qualitative research (Topic 3). The *International Journal of Nursing Studies* focuses on literature search (Topic 1). The leading journal associated with nutrition and health (Topic 14) was the *Western Journal of Nursing Research*. The *Nursing Research Journal* was the leading journal in chronic illness management (Topic 12). The *Journal of Nursing Scholarship* was a prominent journal in qualitative research (Topic 13). *Research in Nursing and Health* represented a relatively high percentage in statistical analysis (Topic 2).

Word clouds are exhibited under two groups (see [Figure 1](#)): research method topics and nursing research topics. The dot at the end of some terms in word clouds indicates stemming or lemmatization when constructing the term list, reducing words to their roots. In word clouds, the font size is based on the term frequency-inverse document frequency scores; the higher the term frequency-inverse document frequency value, the larger the font size for that term. The top three references with the highest topic scores for the 18-topic models are provided in Appendix [S5](#). Given that these three references are the most representative of their respective topics, they will provide additional information on each topic. When determining the topic of a particular study, the study was assigned to the topic with the highest subject score/loading. Therefore, each study is devoted to only one topic.

[Figure 2](#) exhibits the trends in nursing research journals. Topic proportions and topic trends are evaluated annually. Notably, three topics (T-3, T-5, T-7) with topic proportions of 8% and above are clearly distinguished from the others. Concept analysis (T-5) was the most dramatically descending topic, with a proportion ranging from 25% to 10%. Advanced practice (T-7) varied between 17% and 8%. Finally, qualitative research (T-3) changed the least and remained current with its course at between 17% and 13% between 1998 and 2021. The other topics include 15 topics with topic proportions between 0.4% and 7%. These topics can be examined separately as uptrends, downtrends and stable trends as research methods and nursing research topics. Qualitative research (T-3) and concept analysis (T-5), which are among the research method topics, were in a downtrend, whereas literature search (T-1), statistical analysis (T-2), randomized control trials (T-8) and quantitative research (T-4) topics were in an uptrend. Among the nursing research topics, advanced practice (T-7) was in a downtrend, and nurse practice environment (T-9), risk assessment (T-10) and nursing science (T-13) were in an uptrend. Nursing satisfaction and burnout (T-6), neonatal care (T-11), chronic illness management (T-12), nutrition and health (T-14), infection control (T-15), maternal nursing care (T-16), sleep quality among nurses (T-17) and geriatric care (T-18) exhibited stable trends.

The results for the top three most common topics (T-3, T-5, T-7) are summarized in the following paragraphs. These three detailed topic examinations can be used to interpret the remaining topics' results using [Table 2](#), [Figure 1](#) and Appendix [S5](#).

3.1.1 | Topic 3: Qualitative research

The qualitative research topic includes 1865 references and 12.4% of the entire corpus of 15,085 references ([Table 2](#)). The two journals that contributed the most to this topic were the *Journal of Advanced Nursing*, with 1114 references, and the *International Journal of Nursing Studies*, with 318 references. The lowest contributing journal was *Nursing Research*, with 65 references ([Table 2](#)). The terms with the highest frequency-inverse document frequency scores in Topic 3 were interview, theme, in-depth interviews and transcribed

TABLE 2 Distribution of abstracts across six journals by topics and their corresponding frequencies.

Topic	ID	Label	Journal						Group/topic	
			JAN	IJNS	WJNR	NR	JNS	RINAH	Total	%
		Research method topics	3385	1449	517	363	390	357	6461	42.9
Topic 1	T-1	Literature search	554	402	51	17	76	11	1111	7.4
Topic 2	T-2	Statistical analysis	316	163	97	122	43	144	885	5.8
Topic 3	T-3	Qualitative research	1114	318	163	65	137	68	1865	12.4
Topic 4	T-4	Quantitative research	139	155	22	28	12	15	371	2.5
Topic 5	T-5	Concept analysis	874	188	84	69	80	57	1352	9.0
Topic 8	T-8	Randomized control trials	388	223	100	62	42	62	877	5.8
		Nursing research topics	3320	1675	1012	944	879	794	8624	57.1
Topic 6	T-6	Nursing satisfaction and burnout	417	199	90	62	84	68	920	6.1
Topic 7	T-7	Advance practice	815	276	16	3	32	3	1145	7.6
Topic 9	T-9	Nurse practice environment		149	150	91	51	99	605	4.0
Topic 10	T-10	Risk assessment	273	200	45	93	52	37	700	4.6
Topic 11	T-11	Neonatal care	166	104	21	79	12	38	420	2.8
Topic 12	T-12	Chronic illness management	297	127	120	150	76	115	885	5.9
Topic 13	T-13	Nursing science	232	52	148	123	238	70	863	5.7
Topic 14	T-14	Nutrition and health	130	63	223	143	73	122	754	5.0
Topic 15	T-15	Infection control	254	157	68	69	89	58	695	4.6
Topic 16	T-16	Maternal nursing care	239	107	90	90	53	116	695	4.6
Topic 17	T-17	Sleep quality among nurses	77	68	33	34	19	47	278	1.8
Topic 18	T-18	Geriatric care	271	172	67	47	52	55	664	4.4
		Total	6705	3124	1529	1307	1269	1151	15,085	100
		%	44	21	10	9	8	8	100	

Abbreviations: IJNS, International Journal of Nursing Studies; JAN, Journal of Advanced Nursing; JNS, Journal of Nursing Scholarship; NR, Nursing Research; RINAH, Research in Nursing and Health; WJNR, Western Journal of Nursing Research.

(Figure 1). The most representative articles of Topic 3 were mainly qualitative studies focusing on the experience of being a close relative of a person who has had a stroke after discharge from the rehabilitation clinic (Backstrom & Sundin, 2009), troubled conscience experience of registered nurses and nurse assistants in elderly care (Juthberg & Sundin, 2010), and living on the border between life and death (Sert et al., 2021) (see Appendix S5).

3.1.2 | Topic 5: Concept analysis

The concept analysis topic explains the variation of the whole corpus. It comprises 9% of the 15,085 references, including 1352 references (Table 2). The journals that provided the highest number of articles in Topic 5 were the *Journal of Advanced Nursing* and the *International Journal of Nursing Studies*, with 874 and 188 references, respectively. *Research in Nursing and Health* contributed the least, with 57 references (Table 2). The terms with the highest topic scores in this topic were concept analysis, philosophy,

literature and theory (Figure 1). The first three articles with the highest topic scores were related to philosophical inquiry in nursing (Pesut & Johnson, 2008), paradigms used for nursing research (Weaver & Olson, 2006) and concept analysis (Risjord, 2009) (see Appendix S5).

3.1.3 | Topic 7: Advanced practice

The advanced practice topic explains the variation and comprises 7.6% of the entire corpus, with 1145 documents. The following journals contributed the most to this topic: the *Journal of Advanced Nursing* and *International Journal of Nursing Studies*, with 815 and 276 references, respectively. On the other hand, the lowest contribution was provided by *Nursing Research Journal* and *Research in Nursing and Health*, with three abstracts for each journal (Table 2). Figure 1 indicates that the United Kingdom, England, National Health Service, workforce, and nurse prescription had the highest term frequency-inverse document frequency scores in this topic. National Health

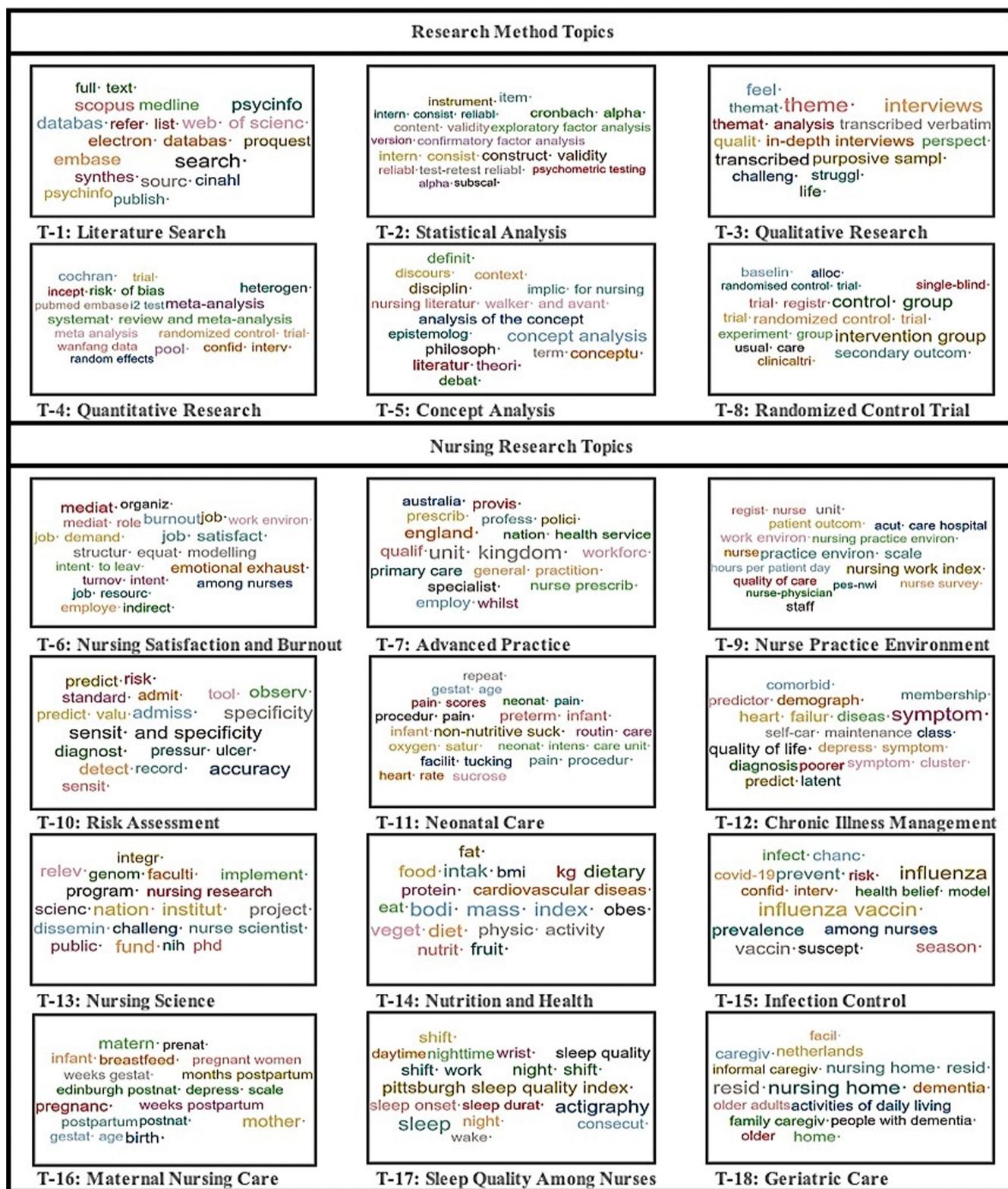


FIGURE 1 Topic word clouds (larger fonts indicate higher term frequency-inverse document frequency values for each term, and similar colours indicate similar term frequency-inverse document frequency values).

Service cadet programmes calculating the costs of work-based training (Norman et al., 2008), National Health Service cadet professional healthcare education (Watson et al., 2005) and nurse prescribing of medicines in Western European and Anglo-Saxon countries (Kroezen

et al., 2012) are some of the research areas in the first three articles with the highest topic scores (see Appendix S5).

Figure 3 shows nursing research journals' significant clusters and word network connections. Based on the network analysis, it

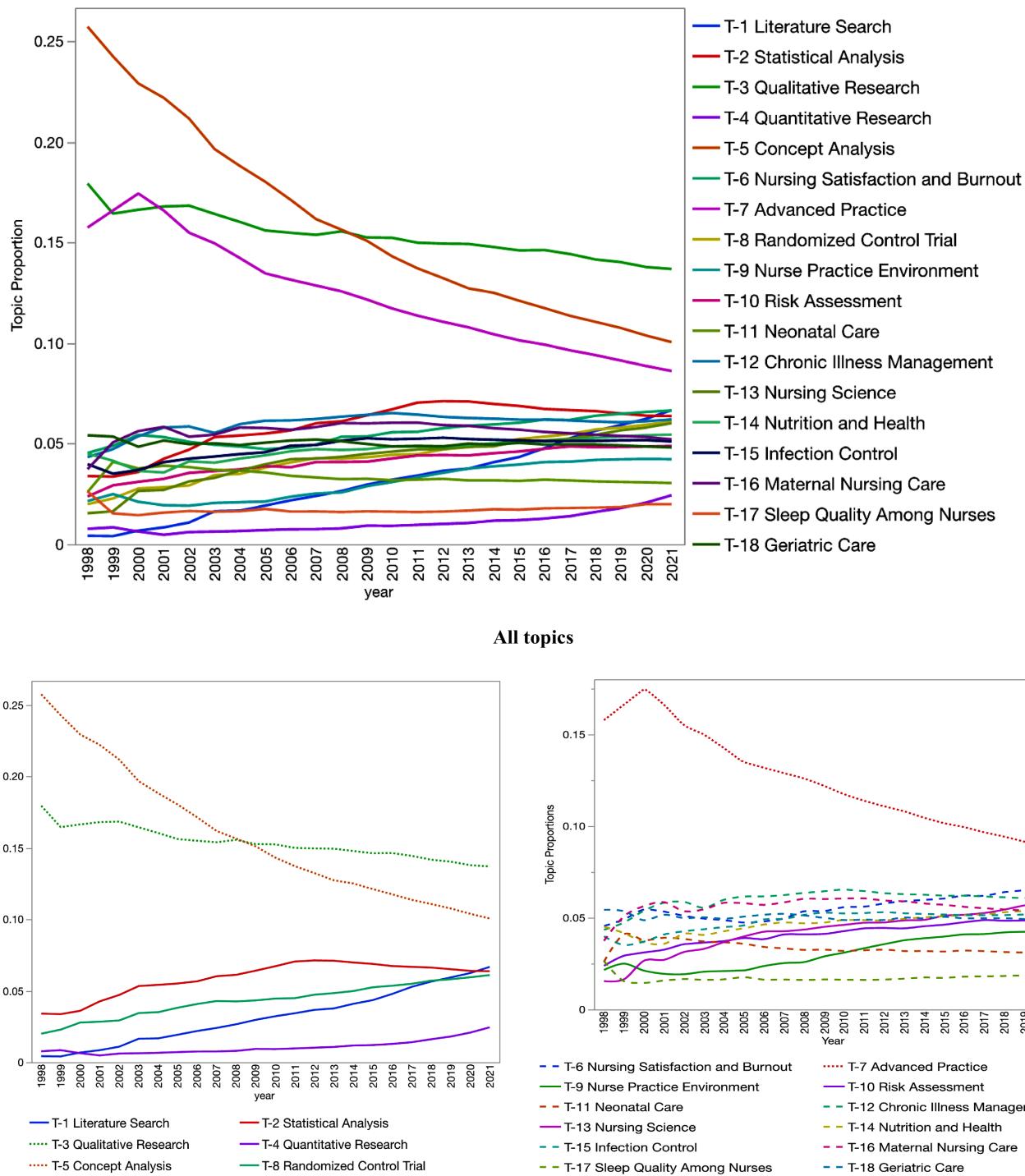


FIGURE 2 Topics showing all trends as measured by the proportion of references from a specific topic in a particular year.

was determined that nurse practice environment (T-9), nurse satisfaction and burnout (T-6), chronic illness management (T-12), risk assessment (T-10), quantitative research (T-4), randomized control trials (T-8) and infection control (T-15) were networked with each

other. This connection is gathered in four main clusters. The infection control cluster is centrally located, connecting all networks. The nurse practice environment, nurse satisfaction and burnout topics form clusters by connecting with the term "work environment"

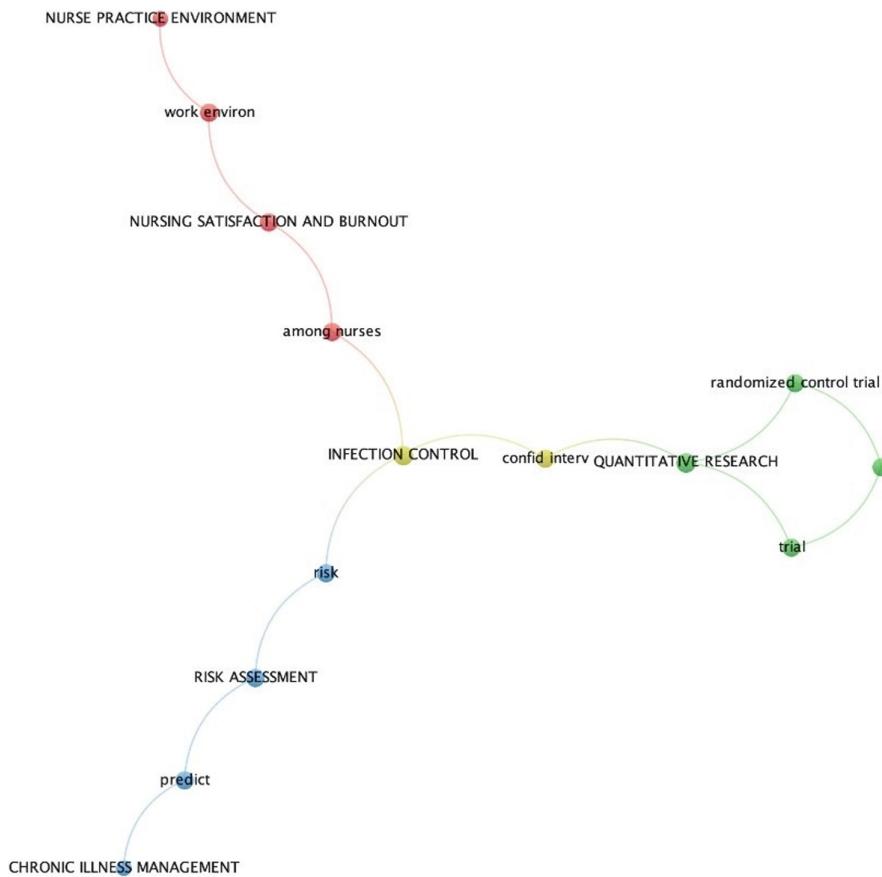


FIGURE 3 Graph representation of word network. Each colour represents a major cluster.

(Cluster-1); the quantitative research and randomized control trials topics with the terms “randomized control trial” and “trial” (Cluster-2); the chronic illness management and risk assessment topics with the word “predict” (Cluster-3). The infection control topic, at the centre of all network analysis, connects with the first cluster through the term “among nurses,” with the second cluster through the word “confidential interval,” and with the third cluster through the word “risk.” The network analysis results can be used to interpret the relationships between the topics using [Figure 3](#) and Appendix S6.

4 | DISCUSSION

In this study, we aimed to identify the most common research topics studied by researchers in the nursing field and analyse their trends between 1998 and 2021. First, we identified these topics using text mining strategies and grouped them according to their similarities. Then, these groups were given topic area names with the help of field experts.

This study showed that the most commonly researched topics could be grouped under 18 labels based on their similarities. However, when researchers submit their studies, they identify their research methods and tools in their abstracts. Therefore, topic areas with words related to research methods and tools, such as ‘validity’, ‘database’, ‘purposive sampling’ and ‘control group’, would be

unusually high. Thus, topic areas related to research tools are separated from the actual research topics. Topic areas that have words related to research topics are listed under the category of ‘nursing research topics’ and the topic areas with research methods and tools under ‘research method topics’. Creating two categories enabled us not only to show the most common topics studied but also to see the methods researchers used to study them.

The research method topics category includes Topic 1: literature search, Topic 2: statistical analysis, Topic 3: qualitative research, Topic 4: quantitative research, Topic 5: concept analysis and Topic 8: randomized control trials. The domain area concept analysis (Topic 5) had the most significant decrease among all topic areas in this category since 1998. Concept analysis comprised a little over 25% of all the articles in 1998 and only 10% in 2021. In this domain, concept analysis, philosophy, literature and theory were the most common words in the word cloud ([Figure 1](#)). Conceptual work and theory development are essential to developing nursing knowledge (Rodgers et al., 2018). Nursing professionals, especially in the last 15 years, have been using concept analysis and developing theories to build knowledge (Roy, 2018). As Roy (2018) argued in her article titled ‘Key Issues in Nursing Theory’, it is tough to build knowledge and conduct research without theory. However, according to our study, this domain area has steadily declined since 1998. Unfortunately, we do not have much evidence about why such a trend is occurring in the literature. It might be related to researchers using defined

concepts and theories instead of creating new ones in their studies. Although interest in using tools of concept analysis is trending down, it remains around 10%, which is still higher than four of the six domains in this category. It would be beneficial for researchers to conduct studies similar to ours in the future to see whether this decline will continue.

Another topic area in this category worth mentioning is qualitative research. It comprises 13% of the entire corpus of 15,085 articles and has been consistently popular since 1998. In this topic area, words such as interview, theme and in-depth interviews are the most common words in the word cloud (Figure 1). The second-highest topic area was consistently high, with no significant change between 1998 and 2021. Therefore, it is safe to say that nurses' long-time interest in qualitative research will continue for the foreseeable future. Given the holistic nature of the profession, it is not surprising that researchers in this field would favour qualitative research tools to answer their questions. However, what is very interesting is how much researchers use qualitative research compared to quantitative research. According to our findings, although there has been a 1% increase in quantitative research tools and randomized controlled trials since 2019, the combination of these two research topic areas only has an 8.3% topic proportion and is still behind qualitative studies. Thus, it would behove future researchers to conduct more studies to find the reasons, as well as perform a risk–benefit analysis of having comparable low quantitative research and randomized controlled trials studies compared to qualitative ones.

The second category, nursing research topics, includes areas related to the most studied nursing topics since 1998. We identified 12 topic areas in this category: Topic 6: nursing satisfaction and burnout, Topic 7: advanced practice, Topic 9: nurse practice environment, Topic 10: risk assessment, Topic 11: neonatal care, Topic 12: chronic illness management, Topic 13: nursing science, Topic 14: nutrition and health, Topic 15: infection control, Topic 16: maternal nursing care, Topic 17: sleep quality among nurses and Topic 18: geriatric care. One of the most critical topic areas in this category is advanced practice. It comprised 8% of the entire corpus in 2021 and has been the most researched topic since 1998. This topic area includes words such as the United Kingdom and its government-funded medical and healthcare system, the National Health Service, nurse prescription, primary care and general practitioner in its word cloud. Although it steadily declined, it is still the most researched topic. Therefore, it is clear that understanding the role of advanced practice nurses and trying to evaluate the efficiency of their services is receiving much attention in the United States and other countries, such as Australia, England and other Anglo-Saxon countries. The concept of nurse prescribing has been one of the most controversial issues in health care since the first nurse practitioner school was established in Colorado in 1965 (Saver, 2015). In the United States, the conversation about nurse practitioners has ramped up, especially after the foundation of the American Academy of Nurse Practitioners in 1985.

Moreover, it became a hot topic after the Balanced Budget Act of 1997, which allowed nurse practitioners to bill directly to Medicare (Saver, 2015). This study shows that nurses' interest in advanced

roles, such as serving as primary care providers and prescribing medication, peaked around 1999 and is still one of the most researched topic areas (Figure 2). Knowing more about advanced practice nurses helps professionals define their scope of practice more clearly and emphasize contributions to health care, such as providing safe and effective care (Sangster-Gormley et al., 2013). According to our study, interest in knowing about advanced practice nurses will be around for a long time.

The nursing science topic is another area that has been in an up-trend since 1998 in the nursing research category. This topic area includes words such as fund, Doctor of Philosophy, nursing research and implementation. The nursing science topic area occupied only a little over 1% in 1998. Since then, it has steadily increased yearly and comprised 6% in 2021. This percentage makes nursing science the fourth most significant topic area in this category. Nursing as a science has come a long way. One of the biggest reasons is the efforts to keep nursing separate and equal from other disciplines.

According to a critical report published by the Institute of Medicine in 2011 titled 'The Future of Nursing: Leading Change, Advancing', it is strongly recommended that nurses should be equal partners with other healthcare professionals, such as physicians. However, this can only be achieved if the nurses see their profession as a science and are interested in research activities. Perhaps for this reason, this landmark report lists evidence-based practice as one of the must-have competencies. Nursing programmes have always included research classes in their undergraduate and graduate programmes' curricula. Also, a Doctor of Nursing Practice, a clinical doctorate emphasizing quality improvement studies, is available to nurses in the United States along with a Doctor of Philosophy. All these decisions to emphasize the importance of research paid off, as evidenced by the nursing science topic being the fourth largest topic area in these six major journals. According to our findings, nurses appear to be interested in research studies. Therefore, the sustainability of nursing as a separate discipline and equal to other professions is secure. Nursing schools should continue emphasizing the importance of research in their curricula. Also, institutions would benefit from allocating funds for nurses with Doctor of Nursing Practice degrees to conduct quality improvement studies in their facilities.

Another topic area that has remained steadily high since 1998 is the risk assessment topic. Assessment is the first step in the nursing process (Robbins, 2021). It is a critical component of clinical reasoning that is crucial when providing safe and effective care (Bail et al., 2020). Properly assessing and documenting risks such as sepsis, falls and pressure ulcers are vital in decreasing hospital length of stay, increasing the quality of care and reducing the mortality rate (Bail et al., 2020). These are a few of the essential key performance points in how hospitals are being judged regarding their rankings. Therefore, interest in learning more about risk assessment is expected to continue. Thus, it would benefit healthcare institutions and future researchers to conduct more studies on risk assessments more effectively and create more risk assessment tools for nurses.

The nurse practice environment is another topic area that we should pay close attention to. Topic area nine comprises 4% of

the total corpus and has been trending upward since the 2000s. Especially when combined with the other topic areas in the same network (Figure 3), such as 'nursing satisfaction and burnout' and 'sleep quality among nurses', the thematic cluster comprises 12% of the topics, making it the largest area of interest. The word network of all these topic areas indicates that there has been an increased concern about nurse staffing. The nursing shortage, defined as the difference between the current and projected supply, has been a widely known problem and a worldwide crisis since the last decade (Buchan et al., 2015; Goodare, 2017). However, as Buchan et al. (2015) argued, this problem in the profession cannot be remedied by training more nurses. As our word network (Figure 3) suggests and Goodare (2017) argued, stakeholders should focus on retention rather than recruiting. The most highlighted reason is that 30%–50% of new nurses tend to leave or change their positions within the first 3 years of their clinical careers (MacKusic & Minick, 2010). Also, it is thought that the average length of a nurse's career is fewer than 5 years. Therefore, as our study points out, addressing the issues that drive nurses out of the profession, such as the nursing environment and burnout, should receive priority attention from stakeholders.

The findings of this study highlight important topic trends in both research tools and research topics in the nursing profession. In research tools, it is apparent that nurses tend to favour qualitative over quantitative or randomized control trials studies. In research, topic areas reveal some essential issues that stakeholders should notice. First, it appears that the interest in learning more about advanced practice nurses is here to stay. Also, the importance of risk assessment and nurses' ability to predict problems and intervene promptly is another topic from which the field would benefit. The last but most important area is the nurse practice environment, which connects with other topic areas, such as nursing satisfaction and burnout and sleep quality among nurses. This network of topic areas is statistically significant because it may give stakeholders clues about why nurses leave the profession and remedies for the nursing shortage.

Even though in this study, we focused on the major topics, when we ran the analyses for a 30-topic model, we identified some emerging or less frequently explored topics in nursing research such as diversity, equity, inclusion and belonging (DEIB), smoking, self-care management, pain management and pressure ulcer (see Appendix S7 for the full list and the associated terms for these topics).

5 | LIMITATIONS

This study has several limitations that should be considered. First, the focus was on six Q1 and Q2 journals with the highest H-index and Scientific Journal Rankings scores, excluding clinical practice journals and nursing specialty journals; therefore, the study only included some of the literature within the nursing discipline. However, given the quality and historical richness of the six journals with categories Q1 and Q2 included in this study, more than 15,000 references were included from the nursing discipline in our corpus, which provided a representative sample. The results from such a large

sample provide valuable information about the current research position within the nursing discipline. This research can be improved by including all nursing journals in future studies. The second limitation is the collection of data between the years 1998–2021. The nursing research domain has a very long history; however, we limited our study period to 23 years (1998–2021) to capture the impact of major changes during past two decades. Since the late 1990s, we have witnessed significant global events such as the rise of technology and internet usage, and the widespread adoption of social media. These events have deeply influenced societal behaviours, adaptation to technology and communication patterns. During these years, notable advancements have been made in technologies such as smartphones, artificial intelligence and big data analytics. The decision to study this timeframe was made with the consideration that it will provide an opportunity to comprehensively analyse how technological innovations have shaped data collection methods and their diverse impacts across nursing research. Third, in the study, analyses were performed on the abstracts. Considering that abstracts contain more keywords than other parts of articles (Shah et al., 2003), using abstracts to create topics was a methodologically appropriate strategy. Using the full-text corpus instead of abstracts in future studies may offer a more comprehensive method for subject modelling algorithms. Another limitation is related to the topic modelling preference. Efficient use of time and human resources comes to the fore in modelling the subject for a corpus of 15,085 research articles. We encourage researchers to use other topic modelling techniques in future studies and compare their findings with our results.

6 | CONCLUSIONS

The aim of this study was to identify and group the most researched topics using text mining strategies and analyse their trends between 1998 and 2021. Knowing what has been researched by nursing research experts would give stakeholders a good understanding of the current issues in the nursing field. It would also guide researchers on where to allocate their finances and efforts.

It was necessary to separate the topic areas related to research methods and tools as they contain words that are not being studied but are used to study other topics. The category of research method topics revealed that nurses tend to favour qualitative studies and have much less interest in concept analysis. Although there is an increased interest in randomized control trials, quantitative studies are well behind qualitative studies. The second category, nursing research topics, indicated the most studied topic areas. Analysis of this category showed that the interest in advanced nursing practice and nurses' ability to prescribe was a large area of interest. We expect that this interest in advanced nursing practice will continue. Another highlight from the nursing research category is the importance of risk assessment; therefore, nursing schools, healthcare institutions and other stakeholders, such as software companies, may emphasize risk assessment in their strategic planning initiatives. Our study's last but most important conclusion is about topic areas related to the nursing practice

environment and their trends. The nurse practice environment is essential, considering that the stakeholders can pinpoint why nurses are leaving the bedside and how to fix the global nursing shortage.

AUTHOR CONTRIBUTIONS

BO, OH and FDZ made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data, involved in drafting the manuscript or revising it critically for important intellectual content, given final approval of the version to be published. Each author should have participated sufficiently in the work to take public responsibility for appropriate portions of the content and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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CONFLICT OF INTEREST STATEMENT

None of the authors has any actual or potential conflict of interest, including any financial, personal or other relationships with people or organizations that could inappropriately influence or be perceived to influence this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available on request from the corresponding author.

ETHICS STATEMENT

Since this study is based on published journal texts, it did not require ethical approval.

ORCID

Beratiye Oner  <https://orcid.org/0000-0002-8004-4657>
Ferhat D. Zengul  <https://orcid.org/0000-0002-8454-1335>

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SUPPORTING INFORMATION

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