Systematic Review and Meta-Analysis

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Thematic analysis of articles on artificial intelligence with spine trauma, vertebral metastasis, and osteoporosis using chord diagrams

A systematic review and meta-analysis

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Abstract

Background: Spine trauma, vertebral metastases, and osteoporosis (SVO) can result in serious health problems. If the diagnosis of SVO is delayed, the prognosis may be deteriorated. The use of artificial intelligence (AI) is an essential method for minimizing the diagnostic errors associated with SVO. research achievements (RAs) of SVO on AI are required as a result of the greatest number of studies on AI solutions reported. The study aimed to: classify article themes using visualizations, illustrate the characteristics of SVO on AI recently, compare RAs of SVO on AI between entities (e.g., countries, institutes, departments, and authors), and determine whether the mean citations of keywords can be used to predict article citations.

Methods: A total of 31 articles from SVO on AI (denoted by T31SVOAI) have been found in Web of Science since 2018. The dominant entities were analyzed using the CJAL score and the Y-index. Five visualizations were applied to report: the themes of T31SVOAI and their RAs in comparison for article entities and verification of the hypothesis that the mean citations of keywords can predict article citations, including: network diagrams, chord diagrams, dot plots, a Kano diagram, and radar plots.

Results: There were five themes classified (osteoporosis, personalized medicine, fracture, deformity, and cervical spine) by a chord diagram. The dominant entities with the highest CJAL scores were the United States (22.05), the University of Pennsylvania (5.72), Radiology (6.12), and Nithin Kolanu (Australia) (9.88). The majority of articles were published in Bone, J. Bone Miner. Res., and Arch. Osteoporos., with an equal count (=3). There was a significant correlation between the number of article citations and the number of weighted keywords ($F = 392.05$; $P < .0001$).

Conclusion: A breakthrough was achieved by displaying the characteristics of T31SVOAI using the CJAL score, the Y-index, and the chord diagram. Weighted keywords can be used to predict article citations. The five visualizations employed in this study may be used in future bibliographical studies.

Abbreviations: AI = artificial intelligence, CJA = category, journal impact factor, and authorship, CP = citation prediction, DS = descriptive statistics, IBP = impact beam plot, RA = research achievement, RD = research domain, SNA = social network analysis, SVO = spine trauma, vertebral metastases, and osteoporosis, T31SVOAI = 31 SVO articles related to AI, WoS = Web of Science.

Keywords: artificial intelligence, bibliometric, citation analysis, osteoporosis, spine trauma, vertebral metastases, Web of Science

1. Introduction

Artificial intelligence (AI) refers to computer algorithms designed to mimic and augment human behavior and thought patterns.[1] Over the past several years, artificial intelligence has been highlighted across a variety of technical industries. Currently, technical terms such as artificial neural networks (ANNs), convolutional neural networks, deep learning, machine learning, and big data are commonly used in everyday conversation.[2]

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The datasets generated during and/or analyzed during the current study are publicly available.

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Highlights:

- T32SVOAI was classified by thematic analysis and visualized by the chord diagram, which is a novel and modern approach.
- There is no literature describing how RAs are calculated using CJAL scores. Bibliometric studies can be made concise, visual, and powerful by the use of the 4-quadrant radar plot.
- We confirmed the hypothesis of a significant correlation between the number of article citations and the number of weighted keywords using the Kano diagram, which can be applied to future relevant studies and bibliometrics at a glance.

1.1. AIs are used in many medical fields, including spines

In many medical fields, artificial intelligence is being used due to the widespread adoption of electronic medical records (EHRs) and the improvement of big-data storage devices in hospitals.[2] There are many applications for artificial intelligence in healthcare, including drug development, health monitoring, medical data management, disease diagnosis, and personalized treatment,[3] such as DXplain, Germwatcher, Babylon, and Watson Health from International Business Machines Corporation.

AI technologies facilitate the efficient and convenient performance of medical practitioners' duties.[2] Artificial intelligence has a wide range of potential applications in medical fields. With machine learning, many attempts have been made to predict the diagnosis and prognosis of various types of spine injuries. The prediction of osteoporotic spines,[4] the occurrence of bisphosphonate-related osteonecrosis of the jaw associated with dental extraction,[5] and bone density[6] are examples of applications of artificial intelligence in the spine field. Despite this, a comprehensive discussion of AIs associated with spine trauma, vertebral metastases, and osteoporosis (SVO) is scarce and difficult to find.

As part of bibliometric analyses, documents can be categorized based on a theme (e.g., osteoporosis, fracture, and deformity), a topical entity (e.g., author or affiliated country), and a characteristic (e.g., citations and publications). Although numerous AI-related bibliographical studies have been conducted,[1,2,7–12] cluster classifications based on themes (or topics) are still lacking.

1.2. Themes by human classification or algorithms

Classification is the process of recognizing, understanding, and categorizing ideas and objects into predefined categories or subpopulations. As part of machine learning algorithms, input training data are used to estimate the likelihood that subsequent data will fall into one of the predetermined categories.[13] Classifying emails as "spam" or "nonspam" is one of the most commonly used classification techniques.

In bibliometrics, articles were classified by humans,[14,15] which is both tedious and time-consuming. To identify the principal components in clusters as themes and leaders, social network analysis (SNA) was applied to cowords.[16,17] Based on this, CiteSpace,[18] HistCite,[19] and VOSviewer[20] are frequently used to assign cluster names based on the most frequently observed keywords[9,21,22] rather than the chief keywords derived from SNA, which is required in this study.

Additionally, SNA has been used to classify keywords and author collaborations in a number of bibliographical studies. There has been no combination of keywords and author clusters to make author clusters meaningful and useful. Thematic classifications are crucial to bibliometrics, which are urgently needed.

1.3. Citation prediction required in bibliometrics

Searching Web of Science (WoS) for titles containing the phrase "100 top-cited" revealed 396 publications. It is common for bibliographical studies to refer to three types of information: descriptive statistics (DS), significant topics or article types with research domains (RD), and research achievements in entities (RA).[14] Based on keywords in articles, citation prediction (CP)[23–26] has been employed in bibliometrics to predict article citations. In this manner, bibliometric analyses can identify study characteristics as well as article citations that are related to their keywords in a particular field of study.[18,27]

1.4. Visualizations are vital in bibliometrics

As mentioned previously, these common bibliographical studies helped us identify the main features that created a distinctiveness in the field as a set of guidelines for physicians and researchers in that particular discipline (such as DS, RD, RA, and CP), but two perspectives are frequently overlooked. There is a lack of: a unique visualization for highlighting the relevant entities on a graph[28,29] (e.g., a four-quadrant plot[30] is more comprehensive than a one-quadrant plot[31]) and a way of predicting the number of article citations using Keywords Plus in WoS displayed on a Kano diagram,[32] which classifies customer preferences into five categories.[33]

There is, therefore, a need to make several breakthroughs to enhance the bibliographical study, including: thematic classifications of articles and clusters and visualizations of citation predictions.

1.5. Study aims

Using bibliometric analysis, this study aims to determine the current position and future direction of artificial intelligence in the field of SVO, as well as: understand the characteristics of articles related to artificial intelligence using visual representation, apply chord diagrams[34] to better understand the theme classification for those SVO articles, and determine whether keyword mean citations can be used to predict article citations in terms of Keyword Plus in WoS.

2. Methods

2.1. Data sources

We searched the Web of Science core collection (WoSCC) for terms such as (TS = "spine trauma" or TS = "vertebral metastasis" or TS = "osteoporosis" or TI = "spine trauma" or TI = "vertebral metastasis" or TS = "osteoporosis" or AB = "spine trauma" or AB = "vertebral metastasis" or AB = "osteoporosis") and TS = "artificial intelligence" and 2022 or 2021 or 2020 or 2019 or 2018 and Article or Review Article and (Endocrinology Metabolism or Orthopedics or Surgery or Clinical Neurology) in WoS research subjects. On October 10, 2022, a total of 31 SVO articles related to AI (denoted by T31SVOAI) were obtained since 2018. The study data are included at the link[35] and deposited in Supplemental Digital Content 1, http://links.lww.com/MD/I172.

As this study did not involve the examination or treatment of patients or review of patient records, it was exempt from review and approval by our research ethics committee.

2.2. Four approaches used in this study

2.2.1. Thematic analysis of RD in T31SVOAI. By using SNA,[16,17] coword analysis was performed to extract the chief components in clusters as themes (or leaders) in keyword (or country-/institute-based author collaboration) networks from the T31SVOAI. Next, articles were assigned with themes (or, say, subject categories) extracted from SNA using equation 1.

$$\text{Theme} = At[\max_{0\le x\le 1}\sum_{i=1}^{L}\sum_{j=1}^{n}(\mathrm{m} < \underset{k\in F}{-m} + 1)] \quad (1)$$

where L is the number of keywords in article i. n is the number of keywords denoted by keyword k belonging to the subject category defined in SNA (i.e., the more coexisting keywords are gathered in an identical cluster). Accordingly, the theme is redirected to the maximal number of keywords (=m) involved in the cluster via equation 1.

In the country-/institute-based author collaboration networks, the cluster names can be assigned using equation 2 based on the themes in articles.

$$Theme_{rj} = \max_{r\ in\ j}(\sum_{n=1}^{N}\sum_{l=1,a\in D,a\in r}^{L}\sum_{j=1,\ t\in c}^{J} term_{rj}(count < -count + 1/L)), \quad (2)$$

where L is the number of terms (e.g., country or institute names in this study) in an article. A contingent table with clusters in a row (r) and themes in column (j) was built to record the summed counts. The term was matched with the cluster number corresponding to the theme defined in an article (e.g., $a \in D$ means the article belongs to a theme) via equation 1. The total weighted scores were summed and selected according to the maximum likelihood in equation 2.

A chord diagram[34] was used to depict the themes mapped for each of the T31SVOAI articles and country-/institute-based author collaborations using their Keywords Plus in WoS, author-defined keywords, and medical subject heading (MeSH terms) in PubMed (linked by their PubMed ID, PMID).

2.2.2. DS. The T31SVOAI[35] since 2018 was dotted on the impact beam plot (IBP)[36] using the citation percentiles (i.e., with the MSExcel function of percentrank()) to display the article impact from 0 to 100 by year (based on normalized citations for each article).

2.2.3. RAs in comparison within entities. A four-quadrant plot[30] was applied to present the influential entities based on the CJAL score[30] determined by the category, journal impact factor, and authorship (CJA) score[37] and the L-index[38] via equations 3 to 5.

$$CJA\ score = \sum_{i=1}^{n} C_i \times J_i \times A_i, \quad (3)$$

$$CJAL\ score = \sum_{i=1}^{n} C_i \times J_i \times A_i \times L - index_i, \quad (4)$$

$$\mathrm{L-index} = \mathrm{round}(\log\left(\frac{Citation}{A_n \times Age} + 1\right), 0), >= 1 \quad (5)$$

Three factors are considered in the CJA scores for a published article: the Category (C; e.g., review, original article, case report, etc.), the journal "quality" (J; e.g., impact factor, JIF, or ranking of the journal), and the authorship order denoted by A). The CJAL score is calculated by multiplying each of these three aspects as well as the L-index (equation 5). CJA scores original research articles higher than other types of manuscripts; co-first authors (denoted RP and FP to compute the Y-index RP + FP[31,39]) score higher than other collaborators; for the journal's quality assessment, they use the JIF or SCI/SSCI journal rankings for SCI/SSCI-indexed papers.[37] SCI/SSCI journal rankings are based on JIF in each research domain; therefore, domain-specific journal rankings are usually not significantly different from those based on JIF.[30,37]

Entities with CJAL scores are shown on a 4-quadrant radar plot.[30] Two types of radar plots were applied to display the top 10 elements in each entity, including those with: journals, themes, WoS categories, and research areas and countries, institutes, departments, and authors by two factors (i.e., RP and FP) on the coordinates. Bubbles were sized by the CJAL score. Accordingly, it is possible to compare the RAs of the top 10 members of each entity with a glance view.

2.2.4. Citation weights used for predicting article citations on CP. The citation weights of Keywords Plus in WoSCC were computed using equations 6 to 11.[40]

$$W_i = \frac{1}{L}, \quad (6)$$

$$\begin{aligned} CiWCD_A \text{ in article A} &= Citation_A \times (\sum_{i=1}^{L-1}\sum_{L=i+1}^{L}(W_i + W_L)) \\ &\div (L-1) = Citation_A \times 2 \times W_i \\ &\times \frac{L\times(L-1)}{2} \div (L-1) \\ &= Citation_A \times 2 \times \frac{1}{L} \times \frac{L\times(L-1)}{2} \div (L-1) \\ &= Citation_A, \end{aligned} \quad (7)$$

$$WCD_A \text{ in article A} = 1.0, \quad (8)$$

The number of keywords in an article is L. The citation weights of each keyword are equal in an article, as demonstrated by equation 7. Without taking into account the citation in existence via equation 8, the weighted centrality degree (CD) for each article equals 1.0.

$$\mathrm{IF}WCD_k = (\sum_{j=1}^{n}\mathrm{CiWCD}_j) \div \quad WCD_k, \quad (9)$$

$$\text{Total Citations of keyword k} = \sum_{k=1}^{n}\mathrm{Ci}WCD_k, \quad (10)$$

$$\mathrm{n} = \sum_{k=1}^{n} WCD_k, \quad (11)$$

Here, n is the number of articles via equations 9 to 11. $\mathrm{IF}WCD_k$ is the mean impact factor (IF) of keyword k. The number of citations in all articles is composed by the summation of individual $IFWCD_k$ in equation 10.

It is worth noting that the computation of $\mathrm{IF}WCD_k$ for keyword k across all articles is based on equal credit in equation $\mathrm{IF}WCD_k$ is used to predict article citations using the Kano diagram.[32,41,42]

For instance, if six keywords are in an article and citations equal 1.0, CiWCD equals 0.83 (=1/6 × (6-1)) when j (=total number of keywords in an article) is six. Similarly, WCD = 0.5 when only one keyword exists, and CD = 0.9 when ten keywords exist. Traditionally, the greater the number of co-occurrences that interact in a network, the higher the WCD in the network. In this study, the WCD is fixed to 1.0 regardless of the number of keywords in an article via equations 6 to 8.[40]

The correlation coefficient (r) was used to determine the predictive power between the weighted keywords and original article citations. The t value of the correlation coefficient (r) was calculated using the following formula $(= r \times \sqrt{\frac{n-2}{1-r\times r}})$[23–26]

2.3. Creating dashboards on google maps

A prediction equation was produced through simple regression analysis using MedCalc statistical software, version 9.5.0.0 (MedCalc, New York, NY). The significance level was set at Type I error (0.05).

All graphs were drawn by author-made modules in Excel (Microsoft Corp). We created pages of HTML used for Google Maps. All relevant CJAL scores for each member can be linked to dashboards on Google Maps. The way to draw visualization involved in this study is deposited in Supplemental Digital Content 2, http://links.lww.com/MD/I173.

3. Results

3.1. Thematic analysis of T31SVOAI on RD

Three chord diagrams[34] were used to depict the themes mapped for each of the T31SVOAI articles and country-/institute-based author collaborations using their Keywords Plus in WoS, author-defined keywords, and MeSH terms in PubMed.

We classified five themes (osteoporosis, personalized medicine, fracture, deformity, and cervical spine) using equations 1 and 2 and illustrated them in Figures 1 and 2. All 31 articles are categorized according to the respective theme. The five themes were, in turn, labeled country-/institute-based clusters.

3.2. Descriptive statistics on DS

Figure 3 shows an IBP developed for T31SVOAI,[35] where red dots represent the largest cluster of osteoporosis. We encourage readers to scan the QR code, click on the dot of interest, and read the abstract of the article on the PubMed website by scanning the QR code. For instance, when the ultimate rightmost dot[4–6] is clicked, three highly cited articles appear immediately.

3.3. RAs in comparison within entities

Figure 4 displays the top 10 elements of entities (e.g., journals, themes, WoS categories, and research areas) in publications

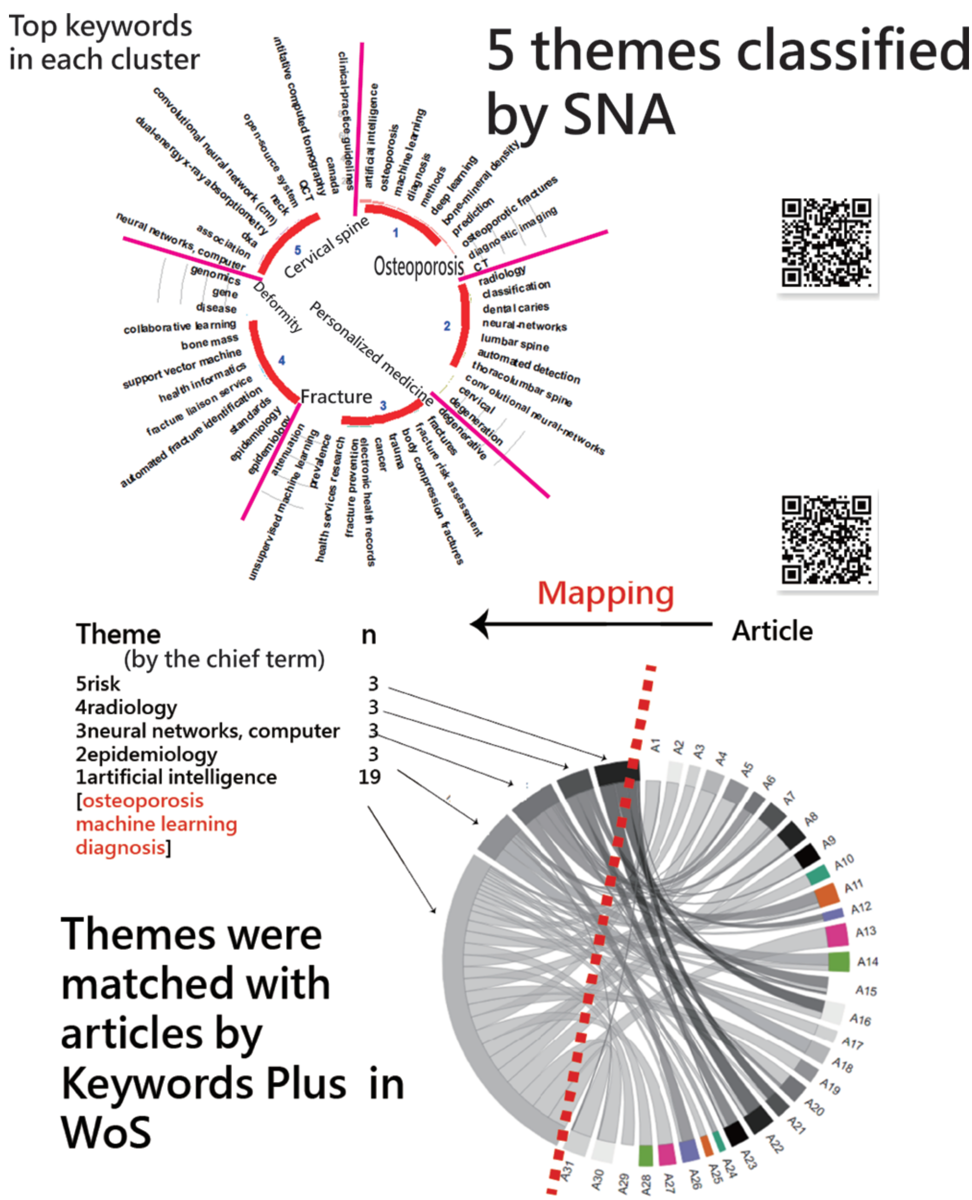

Figure 1. Coword analysis of keywords and relationships between themes and articles shown on the chord diagram.

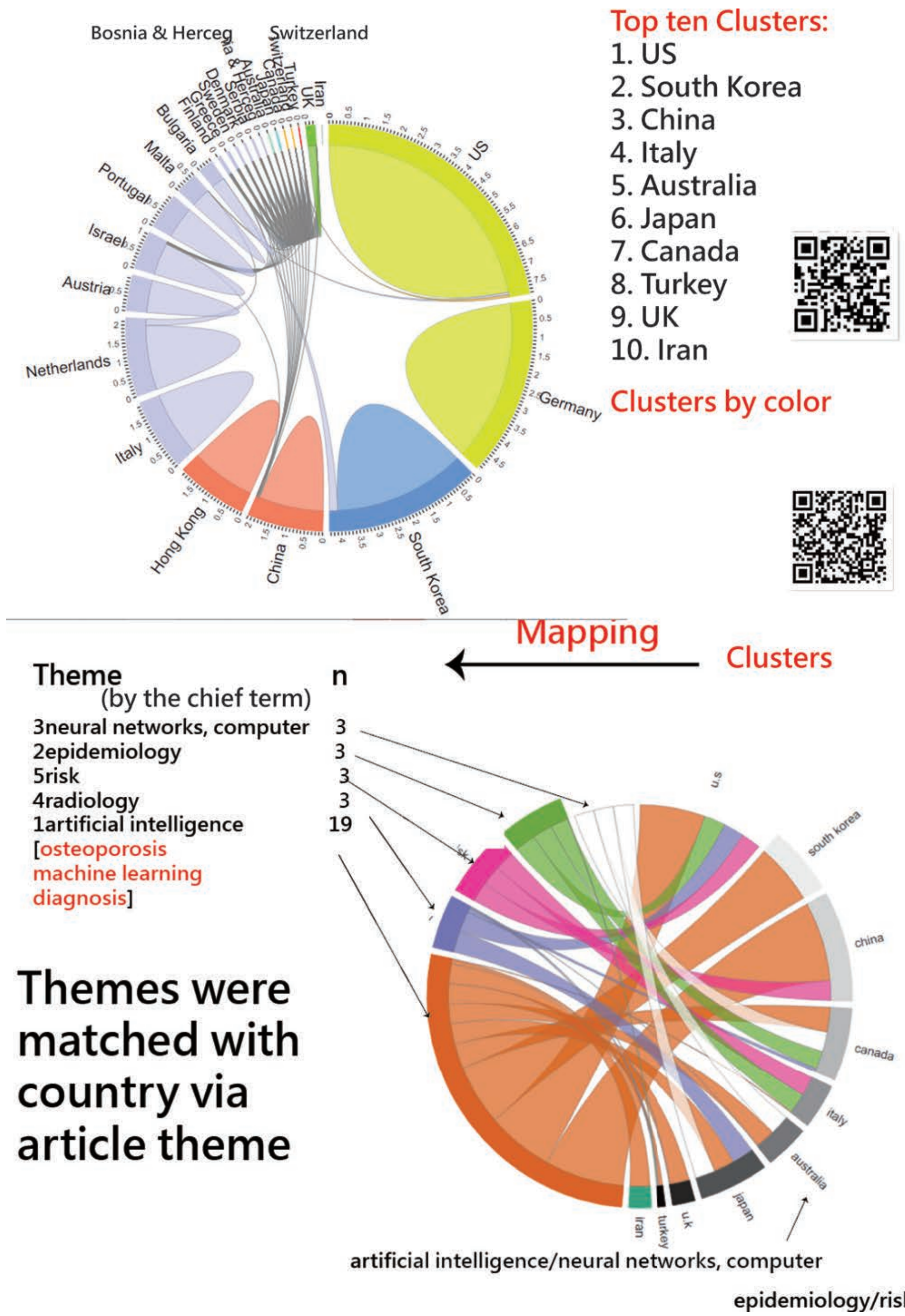

Figure 2. Coword analysis of institute-based author collaborations and the relationship between themes and institute-based clusters shown on the chord diagram.

(from top to bottom) and their mean number of citations in red font. The majority of articles were published in Bone, J. Bone Miner. Res., and Arch. Osteoporosis, with an equal number of entries (=3); artificial intelligence (=19/31 = 61%) in the theme of osteoporosis; endocrinology & metabolism (=20/31 = 65%) in the WoS category; and endocrinology (=20/31 = 65%) in the research area (as defined in the WoS database).

Figure 5 shows that the dominant entities with the highest CJAL scores were the United States (22.05), the University of Pennsylvania (5.72), Radiology (6.12), and Nithin Kolanu (Australia) (9.88). In Figure 5, all of these elements are located by the Y-index (=RP + FP).[31,39]

3.4. Citation weights used for predicting article citations (CP)

There was a significant correlation between the number of article citations and the number of weighted keywords (F = 392.05; $P < .001$), as shown in Figure 6. The prediction linear equation is expressed as $y = -3.3460 + 1.6261 * \text{weights}(x)$ of keywords. All 31 articles were located within the one-dimensional zone in the Kano diagram ($R = 0.96$, df = 29, t = 19.8, $P < .0001$).

3.5. Online dashboards shown on google maps

All the QR codes in Figures are linked to the dashboards.[43–52] Readers are suggested to examine the displayed dashboards on Google Maps.

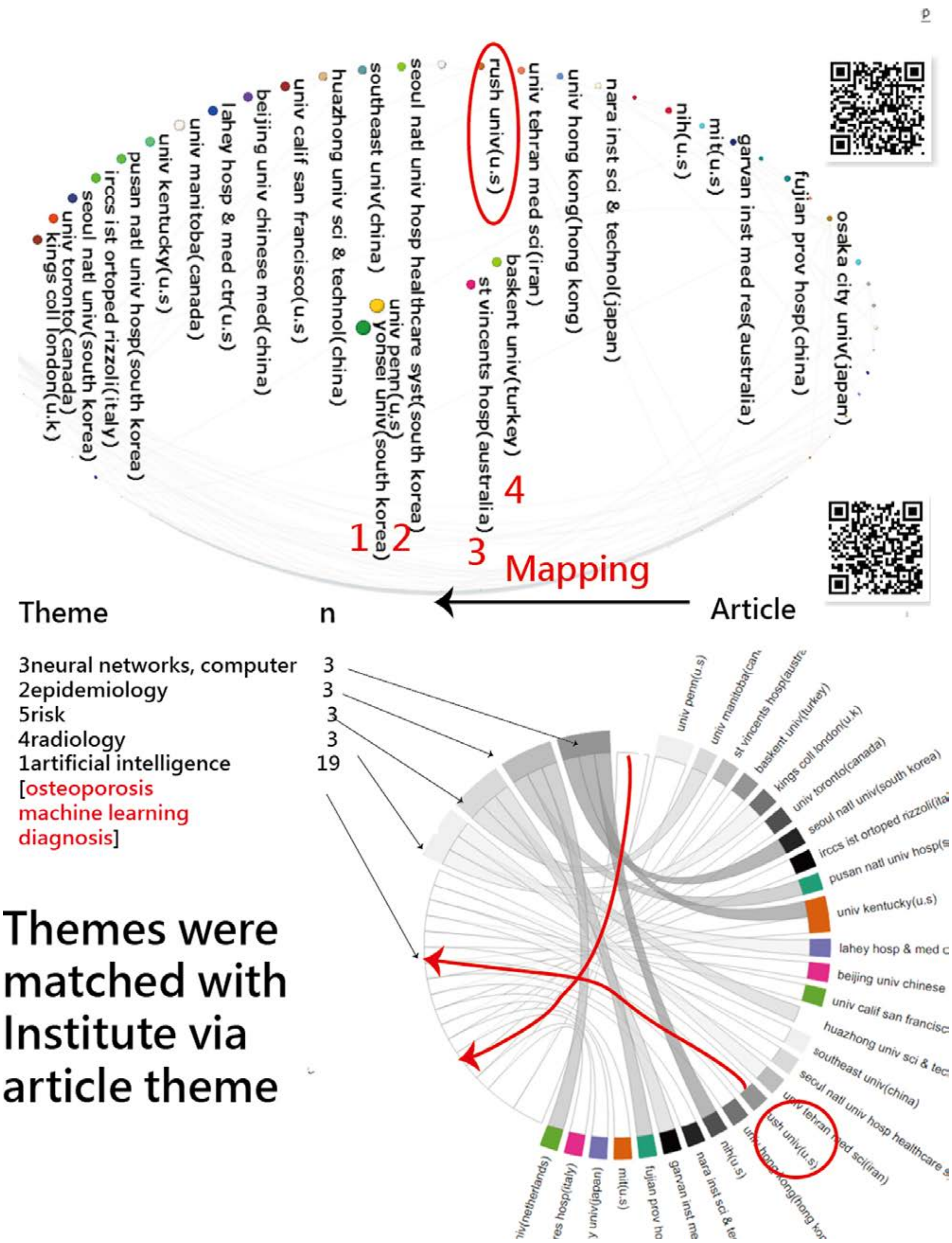

Figure 3. T31SVOAI articles shown on the dot plot (IBP).

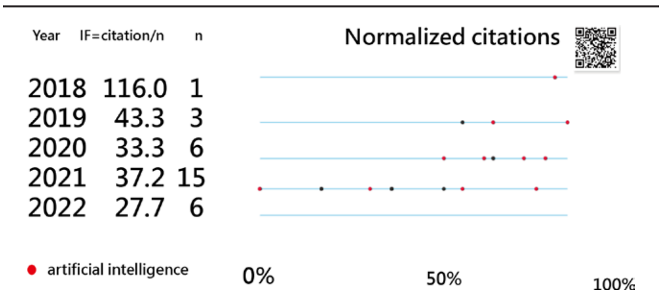

Figure 4. Four aspects of journal, theme, WoS category, and research area in comparison of their publications and mean citations for the top ten elements.

4. Discussion

4.1. Principal findings

We found that there are five themes classified (osteoporosis, personalized medicine, fracture, deformity, and cervical spine) by a chord diagram. The dominant entities with the highest CJAL scores were the United States (22.05), the University of Pennsylvania (5.72), Radiology (6.12), and Nithin Kolanu (Australia) (9.88). The majority of articles were published in Bone, J. Bone Miner. Res., and Arch. Osteoporos., with an equal count (=3). There was a significant correlation between the number of article citations and the number of weighted keywords ($F = 392.05$; $P < .0001$).

Accordingly, the research goals were achieved: understanding the characteristics of T31SVOAI articles, applying chord diagrams[34] to better understand the theme classifications of T31SVOAI articles, and verifying that keyword mean citations can be used to predict article citations in terms of keyword plus in World of Science.

4.2. Chord diagrams used to present the relationship between themes and clusters

The characteristics of 100 top-cited articles are commonly visualized with three categories of information on DS, RD, and

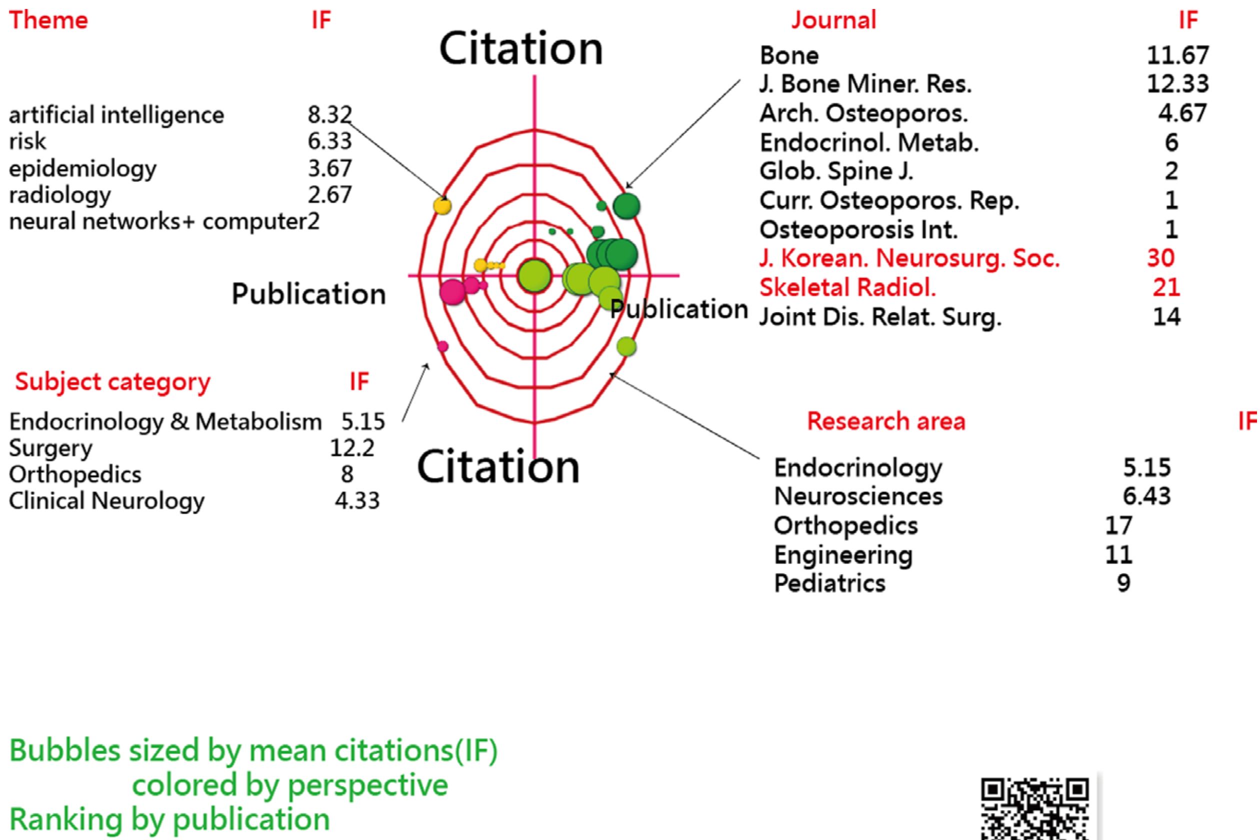

Figure 5. Four aspects of country, institute, department, and author in their publications and CAJL scores for the top ten elements.

RA.[14,18,23–27] Some studies[18,23–27] have applied CP to predict article citations based on the mean citations of article keywords, but the visual presentation is not comparable to the Kano diagram with the unidimensional feature from the left-bottom corner to the top-right corner. Additionally, many articles include many tables and graphs in bibliometrics without applying radar plots and chord diagrams to condense information of interest for readers, as we did in Figures 1 and 2, particularly with the IBP in Figure 3 to display all those T31SVOAIs on a dashboard and save article spaces when compared to those with 50 articles in a study.[2]

Chord diagrams[34] were used to visualize dynamics related to contraceptive use and to bring data into practice. The dashboards (e.g., in Figs. 1 and 2[44,46,48]) provide an easy way to visualize the relationship between themes and clusters. As a result of chord diagrams, we gain a clear understanding of the relationship between two or more entities (e.g., the themes and clusters in Figs. 1 and 2), something that is rare in bibliometric analysis (see them[44,46,48] without these features in spine-related bibliographical studies[14,53–57] previously). Supplemental Digital Content 2, http://links.lww.com/MD/I173 provides the R code for reproducing the chord diagram.

Furthermore, chord diagrams could be used by author collaborations to illustrate their network relationships, such as the two[58,59] with more effective representations than the traditional displays illustrated in Figures 2 and 7.

4.3. CJAL score used to evaluate RAs for entities with T31SVOAI

There are four factors that contribute to the CJAL score: subject category, journal impact factor, authorship in positions on the article byline, and article citations. The evaluation of individual RAs has traditionally been based on bibliometric metrics (e.g., h-index,[60] g-index,[61] x-index,[62] hx-index,[63] author impact factor,[64] Y-index,[42] and hT-index[65,66]). These metrics have a number of disadvantages, such as assuming that all coauthors contributed equally to the article, regardless of the type of document or journal impact factor. The CJAL score[30] bridges the gap between publications and citations when evaluating the RA beyond those bibliometric metrics.

WoS has not yet identified any studies related to SVO based on the CJAL score. The current study on T31SVOAI represents the first attempt to use bibliometric analysis in the field of spine surgery. The dashboard-type 4-quadrant radar plots depicted in Figures 4 and 5 provide a summary of eight important entities rather than tables and graphs in traditional bibliometrics. A unique and modern approach has never been used in the literature before. It is possible to advance bibliometric analysis in this manner in the future.

As seen from the CJAL score, the US dominates the T31SVOAI articles. This study differs from many traditional bibliographical studies in that the publications are computed based on the first and corresponding authors rather than just the first author, as in traditional bibliometric studies. In this study, the US (22.05), the University of Pennsylvania (5.72), Radiology (6.12), and Nithin Kolanu (9.88) were identified as the most influential entities with higher CJAL scores. It is therefore recommended that the CJAL score be used to measure RAs in bibliometric research, particularly when using a radar plot to condense information at a glance.

Traditional bibliographical studies with DS, RD, and RA provided us with a clear understanding of what distinguishes a discipline or field (or topic) from the others and provided insight for physicians and researchers. However, two main concerns were

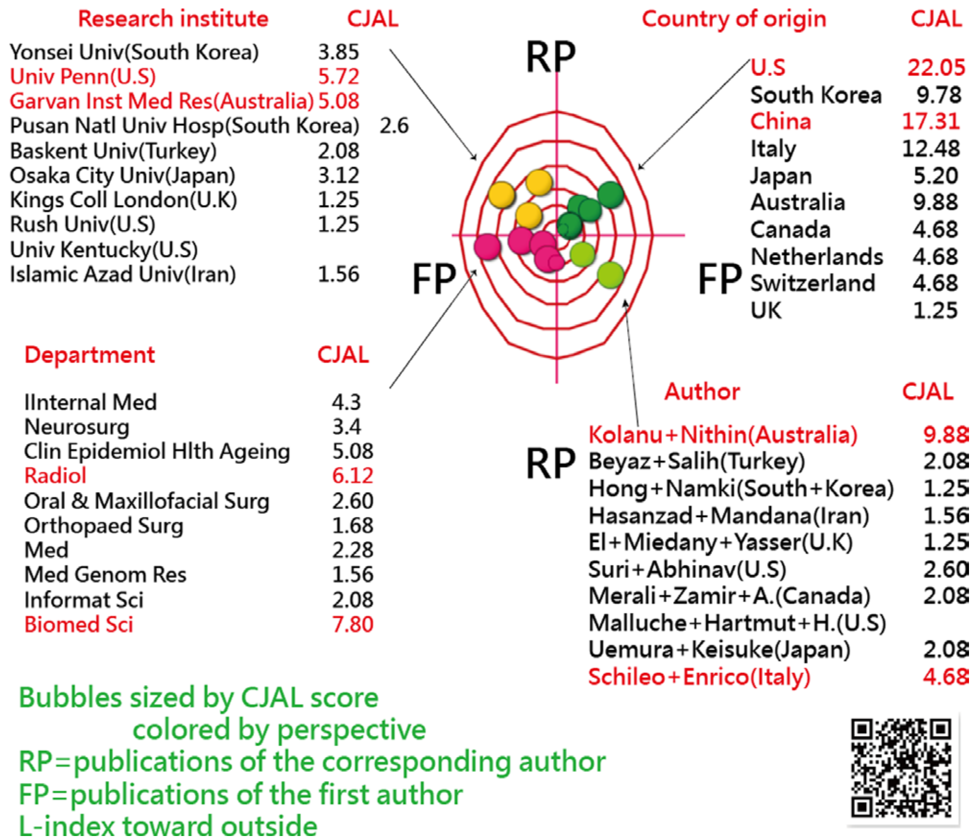

Figure 6. Weighted Keywords Plus to predict article citations, as shown in the Kano diagram (note. $R = 0.96$, df = 29, $t = 19.8$, $P < .0001$)) based on T31SVOAI articles (n = 31).

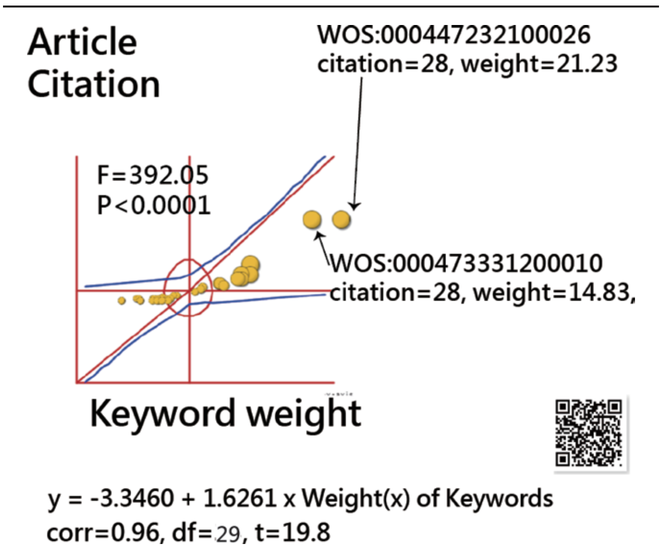

Figure 7. Coword analysis of country-based author collaborations and the relationship between themes and country-based clusters shown on the chord diagram.

frequently overlooked. In such cases, a simplified visualization of all relevant entities is lacking (as in Figs. 4 and 5), and a method for predicting the number of article citations (i.e., citation prediction, CP) using a Kano diagram for the future references is missing.

4.4. Top three most cited articles

By viewing T31SVOAI,[35] the article[4] cited 29 times was authored by Nam (South Korea) et al and classified as the theme of osteoporosis in this study. Machine learning can be used to predict the T-score and osteoporotic vertebrae solely by analyzing the HU of conventional CT images. The study included 70 cases and 198 lumbar vertebrae T-scores for QCT and HU for conventional CT. By using a logistic regression algorithm, the accuracy was 92.5% in distinguishing osteoporotic spines from nonosteoporotic spines. Using the machine learning model, the T-score and osteoporotic vertebrae can be predicted solely based on the HU of a conventional CT, which will assist spine surgeons in not underestimating the osteoporotic spine prior to surgery.

The second most cited article[5] cited 28 times was authored by Melissa L Kim (South Korea) et al and classified as the theme of osteoporosis in this study. A retrospective study of 125 patients with 41 cases and 84 controls was conducted to determine whether bisphosphonate-related osteonecrosis of the jaw (BRONJ) is associated with dental extraction in patients taking bisphosphonates for the treatment of osteoporosis. The performance was analyzed using a random forest model, an artificial neural network, a support vector machine, logistic regression, a decision tree, a drug holiday alone, and a CTX level alone. Compared to conventional statistical methods using drug holidays and serum CTX levels, machine learning methods performed better at predicting BRONJ associated with dental extractions. Thus, machine learning can be applied to a wide range of clinical studies.

The third most cited article[6] cited 20 times was authored by Lee (South Korea) et al, and classified it as the theme of osteoporosis as well. In a study of 334 health checkups, 170 images of abnormal spine X-rays and 164 images of normal spine X-rays, and dual-energy X-ray absorptiometry (DXA), it was determined that the combination of VGGnet feature extraction and random forest classification based on the maximum balanced classification rate (BCR) provided the best performance in predicting spine BMD.

There are other abstracts in T31SVOAI that are included in Supplemental Digital Content 3, http://links.lww.com/MD/I174.

4.5. Implications and possible changes outlined in this study

There are several noteworthy aspects of this study. First, CJAL scores are superior to biometric indices (such as the h-/g-/x-/Y-/hT-/hx-index) because they take into account more aspects of the quality and quantity of the article's features.

Second, with the chord diagram, we were able to highlight entity relationships in a quick manner, which is easy to accomplish in the Rstudio package(see Figs. 1 and 2 and Supplemental Digital Content 2).

The third feature is the use of a 4-quadrant radar plot, which provides readers with a visual representation of four perspectives in article entities at a glance, especially when research achievements are indicated by the CJAL score rather than the Y-index with a single one-quadrant radar plot, as in the traditional study.[31]

Additionally, the Kano diagram can be utilized to identify the trajectory of two variables and to predict article citations based on keywords, which may prove useful in future bibliometric analyses and does not limit bibliometric analysis to DS, RD, and RA, as many traditional bibliographical studies do.

The theme classification using SNA is objective and unique in comparison with previous studies using manual methods.[14,15] Evidence indicates that the classification method is valid and should be recommended to future researchers, particularly when combined with the chord diagram,[34] which illustrates the relationship between themes and clusters. Supplemental Digital Content 2 contains the R codes for drawing the chord diagram.

4.6. Limitations and suggestions

A number of issues need to be examined in further research. The first concern is that the Rstudio package used for drawing the chord diagram is not unique and irreplaceable. It is also possible to draw them using several other software packages.

Second, this study uses Google Maps to display dashboards. Since Google Maps requires a paid project key, these installments are not free. It may therefore be difficult for other authors to replicate the usage within a short period of time.

Third, calculating the CJAL score requires considerable computation. The development of this technology will require dedicated software in the future.

Fourth, it has been recommended that the radar plot and CJAL score be combined to simplify article spaces in comparison to other traditional bibliographical studies with many tables and graphs. However, the RAs are determined by other factors that must also be considered when drawing radar plots in the future.

Fifth, to present the study results, five typical visualizations were used, including Kano diagrams, radar plots, dot plots, chord diagrams, and network plots. It is common for bibliometric analysis to be represented visually in a variety of ways. For future studies, it is recommended that more appropriate visual displays be used to facilitate readers' understanding of the study features.

Finally, even though T31SVOAI articles were extracted primarily from WoS, the results were different for articles retrieved from other databases (such as Google Scholar, Scopus, and PubMed). There is a need for future studies to extract T31SVOAI from a greater number of bibliometric databases.

5. Conclusion

A breakthrough was achieved by analyzing the network characteristics found in T31SVOAI, which included chord diagrams with a demonstration of theme classification. It is possible to identify article themes and predict T31SVOAI citations using Keywords Plus. In future studies, a 4-quadrant radar plot combined with the CJAL score should be applied to 100 top-cited articles instead of focusing only on SVO.

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Author contributions

YP, JCJ and JL provided the concept and designed this study, PH and TWC interpreted the data, and PH monitored the process and the manuscript. TWC and PH drafted the manuscript. All authors read the manuscript and approved the final manuscript.

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