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Applications of Rule-based Systems in Dental Decision Making: Scoping Review

Sara H.Aloufi[1], Mayada A.Alrige[1], and Dalea M.Bukhary[2]

[1]*Department of Information Systems, King Abdulaziz University*

[2]*Department of Oral and Maxillofacial Prosthodontics, King Abdulaziz University*

Jeddah, SA

ssalemaloufi@stu.kau.edu.sa, malraegi@kau.edu.sa, dbukhary@kau.edu.sa

Abstract. this scoping review aims to explore and summarize the application of rule-based systems (RBSs) widely employed in dentistry and to evaluate their performance and practical significance. We conducted a scoping review following the methodology of PRISMA Extension for Scoping Reviews (PRISMA-ScR) on five databases: Web of Science, Scopus, Google Scholar, Saudi Digital Library, and the IEEE Xplore. We searched for literature published in English up to October 2021. Two reviewers evaluated each potentially relevant study for inclusion/exclusion criteria, and any discrepancies were resolved by a third researcher. Out of 303 searched studies, 19 fulfilled this review's inclusion criteria. We identified two domains based on the methodology used in the included studies: (i) uncertainty management approaches employed in the RBS (n = 16) and

(ii) integrating machine learning techniques with the RBS (n = 5). The vast majority of included publications used fuzzy logic to manage uncertainty (n = 11). A hybrid fuzzy RBS and neural network achieved the highest accuracy of 96%. The review also found that periodontology was the most commonly addressed specialty. In an analysis of the current literature, RBSs were found reliable in assisting dental practitioners in decision-making. Clinical decision-making involves a high level of uncertainty, which explains the tendency to use fuzzy logic in RBSs. These systems can also be used as educational tools primarily for both undergraduate dental students and less experienced dentists (e.g., dental interns, postgraduate, and junior dentists) to aid in making reliable decisions.

Keywords—Artificial intelligence, Clinical decision support systems, Rule-based, Expert system, Dentistry.

I. INTRODUCTION

(CDSS), such as expert systems (ESs), to detect dental diseases, and many treatments are

Over the past decade, artificial intelligence (AI) techniques have been widely used in clinical decision-making. Specifically, expert systems (ESs), also known as rule-based systems (RBSs), have proven beneficial in dealing with

provided through them [3]. The results of these reported studies have proven to be efficient and helpful

complex medical and clinical decision-making. A large volume of published studies describes the role of ESs in medical diagnosis, treatment planning, and management [1, 2]. ESs were designed to imitate human-like reasoning by leveraging expert knowledge in a particular domain and storing the information in its knowledge base as rules and facts. Some advantages of ESs include reducing the cost and time of diagnosis, improving the quality of the decision, and in turn improving patient care.

Several studies have applied clinical decision support systems
for dentists to be more precise in diagnosis and clinical decision- making. The use of ESs in the field of dentistry can simplify the dentist's tasks and provide results in a timely manner, which can save time and help them perform their duties more efficiently.

Recently, many review papers have been carried out to cover AI-based models that have been used in dentistry. Their reviews either focus on a specific specialty such as prosthodontics [4] and orthodontics [5] or general areas of dentistry [6, 7]. However, these reviews didn't specifically document the existence of rule-based AI applications. Hence, this scoping review aims to explore and summarize the application of rule-based systems (RBSs) in dentistry and evaluate their performance and practical significance. The authors have attempted to 1) present all research works seeking to
support the decision-making process in different dental specialties,
2) summarize the study findings investigated and the evaluation measurements utilized, and 3) identify gaps in the literature and recommend new directions for future work.

II. MATERIALS AND METHODS

A scoping review of the published literature was based on the methodology of PRISMA Extension for Scoping Reviews (PRISMA-ScR) [8]. As such, in the following sections, we ex- plain the details of the method used to conduct the review accord- ing to the following steps: (1) identifying the research questions,
(2) identifying the relevant literature, (3) selecting articles, (4) an- alyzing articles, and (5) collecting, summarizing, and reporting results.

A Establishing the Research Question

For the present scoping review, the PCC (Population, Concept, and Context) framework recommended by the Joanna Briggs In- stitute (JBI) was used to identify the main concepts in our primary review questions, as can be seen in Table I. This framework was also used to inform our search strategy. The two research questions we sought to answer in this study are:

Q1: What are the applications of RBSs in the field of dentistry?

Q2: How are these applications used in different dental special- ties?

We intend to contribute to the body of knowledge by answering the research questions and providing insight into how RBSs may develop efficient medical decision-making.

Table I. PCC framework

Population	All humans (no restriction)
Concept	The applications of RBSs
Context	Different specialties in the field of dentistry

B Identifying Relevant Studies: The Search Strategy

1) Search Sources

To inform our analysis, the research queries were per- formed in October 2021 across five electronic bibliographic databases, including Web of Science, Scopus, Google Scholar, the Saudi Digital Library (SDL), and the IEEE Xplore. Only studies published after 2010 were included because we wanted the most recent evidence. A hand search was also carried out to ensure that we covered all possible relevant publications by checking the reference lists of the included studies. However, EndNote (version X.9; Clarivate Analytics) will be used to manage the reference data by removing any duplication.

2) Search Terms

The search strategy employed the following search terms in the title or abstract: (“decision support” OR “expert sys- tem” OR “knowledge-based system” OR “rule-based sys- tem”) AND (“dentistry” OR “tooth” OR “dental” OR “pul- pal” OR “orthodontics” OR “periodontitis” OR “maxillofa- cial surgery” OR “dentist” OR “teeth” OR “caries” OR “oral health”).

3) Study Selection

Following the PRISMA-ScR guideline, the study selection was performed for retrieving articles from the databases in two stages. First, titles and abstracts were preliminarily screened against the inclusion and exclusion criteria (see Table II). In the second stage, following title and abstract screening, full texts were reviewed for the remaining studies to exclude further articles that met our exclusion criteria. Two reviewers (SA and MA) independently evaluated both phases, and any disagreements between them about the inclusion or exclusion of an article were resolved through discussion or including a third researcher (DB) to make the final decision.

Table II. Criteria for Study Selection

Criteria	Specified Criteria
Inclusion	- Studies that published from 2010 onwards - Only written in English - Original research - Must be focused on a rule-based approach, and its application - Study results should include measured or quantified outcomes (e.g., accuracy, specificity, sensitivity)
Exclusion	- Review articles - Abstract

Data Extraction and Analysis

This stage was conducted for each included article to extract key information and enter it into an Excel spreadsheet. Study information extracted included author(s), year of publication, clin- ical application, study factors, research objective, the technique utilized, target user, and the performance (metrics used with their results). We used a narrative synthesis approach to analyze the data, summarizing and reporting the findings. Additionally, a de- scriptive statistical analysis was carried out to provide a numerical overview of the range of data.

RESULTS

A Search Results

The initial search strategy yielded 297 potentially relevant pub- lications from Scopus (n = 125), WoS (n = 66), SDL (n = 88), IEEE (n = 13), and Google Scholar (n = 5). Subsequently, six additional articles were found during the backward reference search. One hundred forty-five duplicate articles were removed, leaving 158 articles in the first round of screening of titles and abstracts. We excluded 56 studies that did not meet inclusion criteria in this screening. Of those, 102 were selected for full-text screening. In the second round of screening, 83 articles were excluded, and fi- nally, 19 eligible publications were included in this review. Fig. 1. depicts the PRISMA-ScR flowchart, which illustrates the selection procedure of the articles at each step.

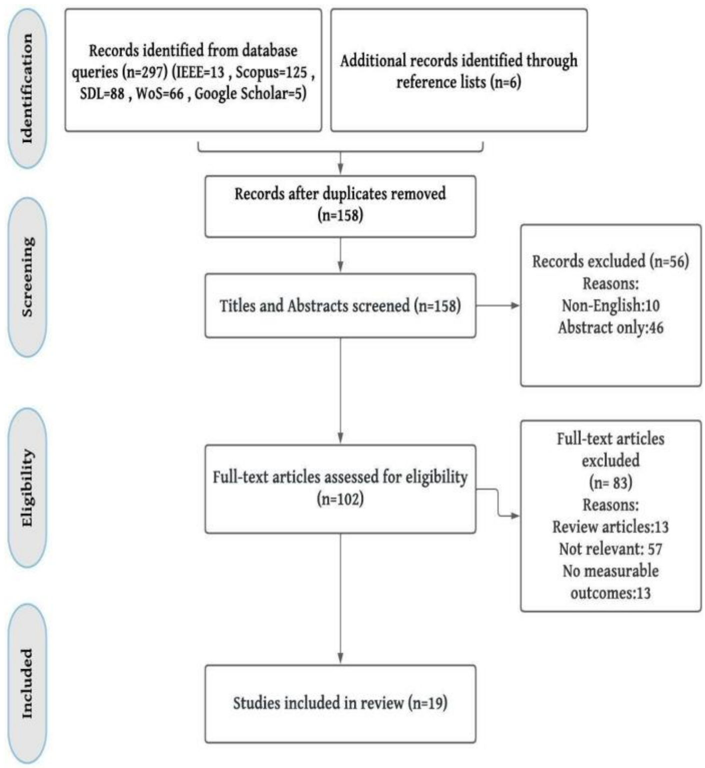

Fig. 1. PRISMA-ScR flow diagram of the search strategy

B Study Characteristics

Analysis of metadata shows that 13 out of the 19 studies (68%) included in this scoping review were published between 2016 and 2021. On the other hand, no publications were found in 2013 and 2014.

With regard to the target users of the publication, it is clear that most of them targeted dentists (n = 12) compared to patients (n = 6). The majority aimed to assist in making decisions regarding diagnosis (11 studies), while three studies focused on treatment planning. Only one article was about detection and classification. The dominant technique employed in publications was fuzzy logic to manage uncertainty in RBSs (n = 11).

The included studies revealed that RBSs have been widely ap- plied in different specialties of dentistry. For instance, nine studies were conducted in periodontology and six in dental anatomy and endodontics. In contrast, a small number of publications were per- formed in other specialties, including dental radiology, cosmetic dentistry, restorative dentistry, oral medicine, and pathology.

C Principal Findings

In this scoping review, the authors have attempted to systemati- cally organize the existing evidence to document the applications of RBSs in dentistry. By synthesizing the data, two domains of rule- based applications were identified based on the techniques used in each study: (i) uncertainty management methods employed in

these systems (n = 16); (ii) machine learning techniques combined with RBSs (n = 5). Table III demonstrates the advantages and disadvantages of each domain.

Table III. Advantages and disadvantages of each technique

Domain	Advantages	Disadvantages
Uncertainty management approaches	• The terms used to report results are in a human-readable format. • The outputs are based on math- ematically proven reasoning and sta- tistical data. • It can handle un- certainty in the RBSs.	• It only works when statistical data is available. • It needs humans to construct and up- date the rules. • It might not be ap- propriate for com- plex issues.
Hybrid CDSS ap- proaches	• It identifies use- ful rules automati- cally. • It is capable of resolving compli- cated issues. • Each subsystem's benefits can be combined to cre- ate a more power- ful system. • It can find hidden relationships be- tween symptoms.	• It requires suffi- cient data to train the model. • It requires a more powerful com- puter. • It needs expertise in machine learn- ing techniques.

1) General Uncertainty Methods Utilized in RBSs

Uncertainty is a fundamental problem that RBSs face and, at the same time, one of the most complex to deal with [9]. Uncertainty refers to the lack of exact knowledge that may arise from incomplete, imprecise, ambiguous, and inconsis- tent data or information, leading to poor decisions. Several theories have recently been developed to handle uncertainty in RBSs, such as Dempster Shafer, Zadeh's fuzzy, certainty factor, Bayes theorem, and so on.[10].

The vast majority of included publications used fuzzy logic to address uncertainty (n = 11). Fuzzy logic is viral in research dealing with vague knowledge [11]. In contrast, the certainty factor technique was introduced in four studies [12, 13, 14,

15]. A certainty factor value reflects the confidence in a given rule, based on the expert's assessment, using numeric and linguistic scales. Certainty factors are preferred if the probabilities are unknown or difficult to obtain. However, few studies implemented the Dempster Shafer method and the Bayes theorem [16, 17].

2) Hybrid CDSS approach (machine learning techniques and RBSs

Designing hybrid architectures for intelligent systems is bene- ficial for making more powerful systems than can be built with either one. The hybrid CDSS approach represents a combina- tion of knowledge-based and machine-learning-based groups. The knowledge-based CDSS models the experts' knowledge in terms of rules in IF- THEN statements. Moreover, the main objective behind hybrid systems is to extract the most valuable characteristics from different artificial intelligence methods and to provide an ideal solution for the problem [18].

A hybrid approach in dentistry has demonstrated good per- formance, as reflected in the two studies done by Tuan et al. in 2016 [19] and 2017 [20]. They applied a combination of fuzzy C-means clustering algorithms and a fuzzy RBS for di- agnosing dental disease from X-ray images. In another study by Osubor and Bello [21], the authors employed a fuzzy RBS with a neural network to diagnose periodontitis. The results reported high accuracy of 96.9%.

Furthermore, Chin et al. [22] developed an intelligent hybrid system by integrating a generative adversarial network (GAN) algorithm with RBS to label tooth dentition and identify root canals. The study revealed that the system was 93.7% accu- rate. In addition, a major study conducted by Senirkentli et al. [23] showed remarkably good performance in diagnosing dental trauma using a combined rule-based and neural net- work approach. Table IV depicts an overview of the main hybrid systems developed for the diagnosis of various dental diseases.

3) Purposes of RBSs in Dental Decision Making

RBSs have been widely utilized in healthcare, notably den- tistry, for clinical decision support purposes, including diag- nosis, treatment, detection, and classification. This section describes all the researchers' initiatives seeking to support the decision-making process and investigates the use of RBS in the different dental specialties (see Table V).

Periodontology The diagnosis of periodontal diseases may require an extended time to record and evaluate the complex- ity and severity of the disease. Therefore, Allahverdi and Akcan [24] designed a fuzzy RBS to determine the severity of the disease based on patient data, including clinical and radiographic findings. They concluded that the system facili- tates the dentist's job with the correct diagnosis and treatment method and speeds up diagnosis with some advantages com- pared with traditional diagnosis and treatment methods.

In periodontology, a full-mouth examination is the most ap- propriate assessment protocol. However, the full-mouth ex- amination process is a time-consuming and exhaustive task for both the dentist and the patient because it requires examin- ing six sites per tooth [25]. To address this issue, Ansarifard and Fakhrahmad [26] introduced a fuzzy RBS to be applied as a tool for partial mouth examination. The authors used a mining scheme to discover hidden relationships among the parameters using the dataset that contains the whole-mouth examination results of about 600 patients recorded by differ- ent periodontists at the Shiraz Dental School. The proposed system uses the rule weight learning method to tune the con- structed rule base. This study revealed high accuracy by computing the MSE values for all features. Thus, this sys- tem is a time-saving and convenient way to improve clinician performance.

Furthermore, due to the difficulty of diagnosing chronic pe- riodontitis, Osubor and Bello [21] aimed to assist dentists in their decisions. Five symptoms were used as inputs: painful chewing, loose teeth, swollen gum, gum that bleeds easily, and pus between teeth and gum. The dataset was collected from the dental clinic of the University of Benin Teaching Hospital. It contained 45 diagnosed data instances, 30 of which were used to train the system while 15 were used in testing. The results were quite promising (96.9%), and the system had better performance compared to other models used in diagnosing periodontitis.

Another example of RBS and certainty factors method to diagnose periodontal disease (gingivitis and periodontitis) was conducted by Zamzami et al. [15]. They found that the results of all 20 cases produced by the experts corresponded with the results of the system diagnosis.

In another study performed by Mago et al. [27], a fuzzy RBS was designed to recognize imprecise and vague values of dental sign symptoms related to a mobile tooth to assist dentists in their decision-making. The comparison of the system's predictions and those of the dentist were similar, meaning that the system will be effective and accurate for making decisions in clinical practice.

Dental Anatomy and Endodontics Diagnosing from panoramic radiographs in dental clinics may be time- consuming since the dentist needs to examine these images to identify the teeth conditions of the patient and treatment planning. Chin et al. [22] proposed a system using GAN and a rule-based algorithm to aid the dentist in identifying dentition, teeth condition, and root canals. They input 200 panoramic radiographs labeled by dentists into GAN as the training dataset, and the remaining 50 images were used for testing. In addition, RBS was employed to predict whether the patient had received previous root canal treatment. How- ever, the experimental results showed that the output provided by the system was close to the judgment of three dentists with 93.7% accuracy. Therefore, the study indicated that this model assists the dentist in diagnosis and gives dentists and patients a faster diagnosis.

In addition, early diagnosis of dental trauma is essential in their management and to prevent further complications. Ac- cordingly, a hybrid system was developed to help general den- tists and dental students in diagnosing and treating traumatic dental injuries according to International Dental Traumatol- ogy Association (IADT) guidelines [23]. The result of this study obtained 78% accuracy.

Table IV. Studies utilizing a hybrid approach

TYPE	Methods used	Performance	
		Metrics	Result
Tuan et al. 2016	Fuzzy RBS and fuzzy C-means clustering	Mean squared error (MSE), Mean absolute error (MAE), and accuracy	MSE is 0.2445, MAE is 0.1264 and accuracy is 90.29%
Tuan et al. 2017			MSE is 0.087, MAE is 0.087, and accuracy is 9l.30%
Osubor and Bello 2019	Fuzzy RBS and neural network	Accuracy	96.9%
Chin et al. 2019	GAN and RBS	Accuracy	93.7%
Senirkentli et al. 2019	RBS and neural network	Root mean squared error (RMSE), MAE, accuracy	RMSE is 0.1384, MAE is 0.0416, accuracy is 78.125%

Restorative Dentistry and Cosmetic Dentistry At present, dental caries are one of the most common tooth problems, especially among young children [28]. It is estimated that 36% of the world population has dental caries, which has in- creased to become a significant public health problem [29]. Singh and Sehgal [30] performed the classification of dental caries. They used 400 dental x-ray images as a dataset, and the features were extracted using Graphics and Intelligence-based Script Technology (GIST). The proposed work clas- sifies caries-infected teeth based on black classification into six classes (Classes I–VI) using six classification techniques. They included a decision tree, a fuzzy RBS, a probabilis- tic neural network (PNN), a K-nearest neighbor (KNN), Ad-aBoost, and Naıve Bayes. The fuzzy RBS obtained 87%
accuracy; the highest accuracy was AdaBoost with 92%.

In addition, Mago et al. [31] designed a fuzzy RBS to help dentists make decisions and minimize inconsistencies when deciding treatment plans for a broken tooth. The system performance revealed that the system's predictions compared with those of the dentist were similar, meaning the system is capable of predicting accurate results.

Hererra et al. [32] aimed to describe the efficacy of bleaching treatments using a fuzzy RBS. The idea was to predict the color change after tooth bleaching based on the Vita commer- cial shade guide. The proposed system has a set of rules in the form of "If the pre-bleaching shade is SHADE 1, then the post-bleaching shade will be SHADE 3." The methodol- ogy contributed to dealing with the uncertainty of the color designation of pre-and post-bleaching colors.

Oral and Maxillofacial Radiology Generally, dentists use their experience to examine dental X-ray images to diagnose potential diseases in dental clinics. How- ever, this process relies on the dentist's knowledge, education, and experience, which varies from one dentist to another. Therefore, Tuan et al., in 2016 [19] and 2017 [20], proposed a model using clus- tering and a fuzzy RBS to diagnose dental problems (cracked, hidden, cavities, missing periodontitis) based on x-ray images (panoramic and periapical). The results of both studies were accurate and demonstrated excellent performance, which sup- ports dentists in making a more valid conclusion.

Oral Medicine and Pathology, and Other Oral Diseases One study proposed a method using RBS and certainty fac- tors to assist in diagnosing five oral diseases (trench mouth, periapical abscess, simplex gingivitis, acute herpetic gingivi- tis, and periodontitis) based on 12 symptoms as inputs. The experimental results reached an accuracy of 99% compared to the expert's diagnosis [14].

Ambara et al. [12] proposed a fuzzy RBS using the cer- tainty factor method to diagnose dental and oral diseases. The system acts as a consultant for the patient by asking sev- eral diagnostic questions rather than utilizing tools that may cause fear or discomfort. The findings indicated that the di- agnostic accuracy was 94.627. An interesting study aimed to increase awareness among the Indonesian population about maintaining their children's oral health. The authors built RBS application to diagnose teeth and oral diseases. The user was given the name of the disease, its definition, pic- tures, and treatment. There is a percentage possibility of being affected by the disease using the Bayes theorem. The performance showed an accuracy of 75% [16].

On the other hand, some studies have diagnosed multiple con- ditions related to different dental specialties. For instance, Parewe et al. [33] designed a fuzzy RBS and evolution strate- gies to diagnose four categories of dental diseases (pulpitis, gingivitis, periodontitis, and advanced periodontitis). As in- put, this study used the diseases' symptoms gathered from observations and interviews with experts. The symptoms con- sidered were plaque, inflamed gums, pain, red gums, swollen gums, easily bleeding gums, wobbly teeth, and breath odor. This method achieved an accuracy of 82%.

In addition, a recent study achieved 95% accuracy using RBS and certainty factors to help users diagnose dental diseases, including periodontal abscess, tooth abrasion, gingivitis, frac- tured tooth, periapical abscess, anodontia, bruxism, purulent gums, perforated tooth, and periodontitis [13].

In a study by Kristian et al. [17], RBS was applied to diagnose teeth and mouth diseases, such as tooth abscess, halitosis (bad breath), gingivitis, dentin hypersensitivity, tartar, caries, mucocele, periodontitis, pulpitis, and mouth ulcer. In testing the system on 10 cases, the results corresponded 100% with the results of the experts.

Likewise, Kamilla and Tanamal [34] designed RBS with the Android platform to diagnose dental and oral diseases (pe- riodontitis, caries, glossitis, pulp necrosis). The proposed platform assists Indonesian people in diagnosing themselves, especially those who live in areas that lack dental care. It also aids the dentist in making the right decisions. Based on testing, the system's performance showed similar results compared to the expert.

Table V. Applications of RBSs in different dental specialties

Specialty	Diagnosis	Treatment	Both	Detection and clas- sification
Periodontology	[14, 16, 18, 22, 27, 34]	[28]	[25, 35]	-
Oral and maxillofacial radiology	[20, 21]	-	-	-
Dental anatomy and endodon- tics	[14, 18, 23, 34]	-	[24, 35]	-
Cosmetic dentistry	-	[33]	-	-
Restorative dentistry	[18]	[32]	[35]	[31]
Other oral dis- eases	[13]	-	[17]	-
Oral medicine and pathology	[14, 15, 18]	-	[35]	-

that oral health qualifies as a serious public health issue [35]. Oral health problems can impact individuals' quality of life to varying extents from functional, social, and psychological aspects in terms of eating, speaking, and smiling. It has been acknowledged that oral health plays an essential role in an individual's general health and well-being [36, 37, 38].

In fact, dental diseases are considered the fourth most expensive disease to treat in most industrial countries; thus, early detection and diagnosis are crucial [18, 39]. In all areas of medicine, in- cluding dentistry, the diagnosis procedure is essential before com- mencing treatment, and an inappropriate diagnosis often results in improper treatment. Therefore, accuracy and the time of diagnosis are crucial to prevent further damage and complicated, expensive, and challenging treatment later.

In this context, AI-based technologies, in particular, decision- making support tools such as RBSs will offer a better solution in dealing with complex medical and clinical decision-making. Generally, RBS is not intended to replace the dentist's judgment and responsibility for decision-making, but rather to assist them in making faster and more reliable diagnoses.

Based on the findings of this review, we found out that the in- cluded studies were applied in various fields of dentistry. However, some specialties such as prosthodontics, pedodontics, orthodon- tics, and forensic dentistry still lack the availability of such systems. For some of these specialties, the knowledge needed to help the dentist make their judgments are too complex, which may require a large number of rules to cover the problem domain. Therefore, building RBSs to serve those specialties would be quite challeng- ing and time-consuming.

However, the significant performance observed in these systems was quite promising and reliable. It can save dentists time, reduce diagnostic efforts, result in higher efficiency, and increase patients' awareness of their oral diseases. Accordingly, this study recom- mends professional healthcare and researchers put effort toward training freshly graduated dentists on how to use these systems effectively in clinical practices and encourages future research to invest in the specialties that have not yet adopted RBS.

In conducting this review, some studies were excluded because they were unavailable in English. In addition, the inclusion criteria and search terms utilized may potentially have led to the absence of other relevant studies. It is recognized that the risk of bias as- sessment has not been carried out since it's not required in scoping reviews [40].

V. DISCUSSION AND IMPLICATIONS

According to the World Health Organization (WHO), nearly

3.5 billion people are affected by oral diseases worldwide, meaning

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تطبيقات الأنظمة القائمة على القواعد في عملية اتخاذ القرار في طب الأسنان: مراجعة النطاق

ساره العوفي[١] ، ميادة الرايقي[٢] ، داليا بخاري[٣]

[1]قسم نظم المعلومات، كلية الحاسبات وتقنية المعلومات

جامعة الملك عبد العزيز ، جدة، المملكة العربية السعودية

[2]قسم إستعاضة الفم والوجه والفكين، جامعة الملك عبد العزيز

جدة ، المملكة العربية السعودية

ssalemaloufi@stu.kau.edu.sa, malraegi@kau.edu.sa, dbukhary@kau.edu.sa

مستخلص. تهدف هذه الدراسة إلى استكشاف وتلخيص تطبيقات الأنظمة الخبيرة أو بما يسمى الأنظمة القائمة على القواعد المستخدمة على نطاق واسع في طب الأسنان وتقييم تهدف هذه الدراسة إلى استكشاف وتلخيص تطبيقات الأنظمة الخبيرة أو بما يسمى الأنظمة القائمة على القواعد المستخدمة على نطاق واسع في طب الأسنان وتقييم أدائها وأهميتها اللعملية. لقد أجرينا هذه الدراسة استنادا إلى منهجية بريزما على خمس قواعد بيانات: ويب أوف ساينس، سكوبس، جوجل سكولار، آي تربل إي والمكتبة السعودية الرقمية. بحثنا عن الأدبيات المنشورة باللغة الإنجليزية حتى أكتوبر ٢٠٢١. قام اثنان من الباحثين بتقييم كل دراسة يحتمل أن تكون ذات صلة بمعايير التضمين/ الاستبعاد، وتم حل أي تناقضات بواسطة باحث ثالث. من بين ٣٠٣ دراسة، حققت ١٩ دراسة معايير الاشتمال الخاصة بهذه الدراسة.

حددنا مجالين بناءً على المنهجية المستخدمة في الدراسات المشمولة: (١) منهج إدارة عدم اليقين المستخدمة في الأنظمة القائمة على القواعد (عدد = ١٦) و (٢) دمج تقنيات التعلم الآلي مع النظام القائم على القواعد (عدد = ٥). استخدمت الغالبية العظمى من الادبيات المشمولة المنطق الضبابي لإدارة عدم اليقين (عدد = ١١). حقق النظام القائم على الواعد الذي يجمع ما بين المنطق الضبابي والشبكة العصبية أعلى دقة بنسبة ٩٦٪. وجدت الدراسة أيضاً أن طب دواعم الأسنان كان أكثر التخصصات التي قد تم تناولها بشكل واسع. في تحليل الأدبيات، كانت الأنظمة القائمة على القواعد موثوقة في مساعدة ممارسي طب الأسنان في صنع القرار. ينطوي اتخاذ القرار السريري على مستوى عالٍ من عدم اليقين، وهو ما يفسر الاتجاه نحو استخدام المنطق الضبابي في هذه الأنظمة. يمكن أيضاً استخدام هذه الأنظمة كأدوات تعليمية لكل من طلاب طب الأسنان الجامعيين وأطباء الأسنان الأقل خبرة على سبيل المثال (أطباء الأسنان المتدربين والدراسات العليا) للمساعدة في اتخاذ قرارات موثوقة.

الكلمات المفتاحية- الذكاء الاصطناعي، أنظمة دعم القرارات السريرية، النظام القائم على القواعد، النظام الخبير، طب الأسنان

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