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Decision support systems for adoption in dental clinics: A survey

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ABSTRACT

While most dental clinicians use some sort of information system, they are involved with administrative functions, despite the advisory potential of some of these systems. This paper outlines some current decision support systems (DSS) and the common barriers facing dentists in adopting them within their workflow. These barriers include lack of perceived usefulness, complicated social and economic factors, and the difficulty for users to interpret the advice given by the system. A survey of current systems found that although there are systems that suggest treatment options, there is no real-time integration with other knowledge bases. Additionally, advice on drug prescription at point-of-care is absent from such systems, which is a significant omission, in consideration of the fact that disease management and drug prescription are common in the workflow of a dentist. This paper also addresses future trends in the research and development of dental clinical DSS, with specific emphasis on big data, standards and privacy issues to fulfil the vision of a robust, user-friendly and scalable personalised DSS for dentists. The findings of this study will offer strategies in design, research and development of a DSS with sufficient perceived usefulness to attract adoption and integration by dentists within their routine clinical workflow, thus resulting in better health outcomes for patients and increased productivity for the clinic.

1. Introduction

The number of dental clinics using information technology has been increasing. Over a decade ago, information systems (IS) in dental clinics were already relatively matured in providing logistic and administrative support [67]. These systems were usually “designed primarily to facilitate administrative functions” centred on billing or at most, automating functions such as appointment alerts and reminders [1]. Though these functions bring about a positive change in the diagnostic behaviour of clinicians, there was still a prominent lack of advisory features such as decision support for clinical functions. This explains the increase in international research interest in the efficient design and adoption of IS and information technology in a typical dental practice [66].

With the potential benefits associated with DSS, it will be exciting to see more research carried out to enable a robust system that can fit within the clinical workflow of the dentist to be used as a diagnostic tool at point-of-care. With this motivation in mind, this paper explores the various barriers that hinder the adoption of clinical decision support by dentists and the key features that dentists desire in a clinical DSS.

There is general consensus that the use of clinical DSS will have potential to improve treatment outcomes [31]. Thus, to fully utilise the computational power of technology within the clinical environment, the use of IS should extend beyond administrative and alert functions to provide advisory functions tailored to the individual patient’s medical and dental condition.

This study has observed that for dentists to adopt a clinical DSS within their workflow, the system should have a reasonably fast response time, be easy to use, and provide information on treatment planning as well as assistance on drug prescription based on individual patient profiles. In order to facilitate drug prescription effectively, a dataset which integrates all available sources is needed. However, besides the work done in [3], no attempt has been made so far in combining all the available drug information into a single dataset [3]. Hence, a system that conforms to our recommendations of a personalised system will contribute to the productivity and efficiency of dental treatment, as well as significantly reducing the occurrence of errors in drug prescriptions. This is crucial as medical negligence can lead to expensive legal suits. With timely and accurate diagnostic treatment planning from such a clinical DSS, more comprehensive treatment options can be made available to patients and practitioners, thus contributing to improved health outcomes for the patient and job satisfaction for the dentist.

This survey will also benefit vendors designing and developing practice management software for dentists. Awareness of the

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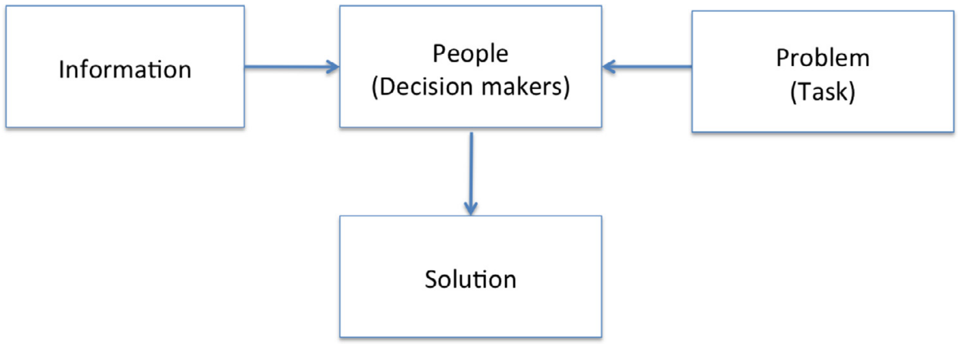

Fig. 1. Design of a typical decision support system.

barriers against adoption of an IS in a dental clinic, the expectations and requirements of dentists for such a system, and important factors such as perceived usefulness, sociocultural and economic factors, and ease of interpretation, will aid vendors in customising a more relevant and efficient system. Providing comprehensive and consistent knowledge through a DSS will result in increased demand for such systems [54].

Besides the contribution to the efficient treatment planning of dentists and assisting vendors in their design of systems for clinical implementation, this paper also has high value for the research community. Understanding the requirements of a clinical DSS that matches the expectations and requirements of dentists will help provide strategies in research agenda and priorities such as methodologies for knowledge reasoning and inference in the context of a dental clinic, thus further enhancing the potential for a seamless integration of a robust, user-friendly and scalable diagnostic tool within the clinical workflow of a dental clinic.

Section 2 continues with a description of the basic structure of a DSS with examples of some recent applications, followed by a brief description of clinical DSS in terms of the basic technology underlying their designs, classifications and benefits in Section 3. Section 4 then highlights some of the barriers facing the user with Section 5 giving a broad survey of current DSS that attempt to overcome these by improvements in interface design, as well as integration of disparate knowledge bases. The paper concludes by discussing future trends in the design of DSS in terms of big data, personalisation and standards, and privacy issues.

2. Decision support systems

Although the focus of this paper is clinical DSS, it is important to understand that these systems belong to the larger group of DSS, where the purpose is to provide decision makers a means to make decisions. Such an understanding from the perspective of general DSS will help support awareness of the functions and features expected of clinical DSS. Fig. 1 illustrates a design structure of a typical decision support system.

When there are more than one decision maker, the process can be complicated, all the more when the information available can be subjective, objective, a combination of both, or even fuzzy. The problem and solution in a dental clinic refers to the treatment that best suits the patient. As shown in Fig. 1, the decision made by the decision maker will depend on the problem itself which would influence the criteria adopted by the decision maker as well as relevant information pertaining to the problem. Such an approach is reflected in the popular PICO model [64] used by doctors in clinical assessment within an evidence-based practice. This framework guides the practitioner in gathering information by asking questions related to information on the Patient (P), Intervention process (I), Comparison with other alternatives (C) and the Outcome to be achieved (O) which is the clinical problem the practitioner is trying to solve or diagnose. In most clinical situations, the patient can also act as the decision maker where information in terms of financial cost and aesthetic demands can influence the final outcome of the decision.

Therefore, a decision making process would normally be influenced by the individual's role as the decision maker, their preferences and the criteria used to make the decision [37,39].

Generally, such complex decision making structure is determined by classical decision theories such as classical formal and empirical-cognitive decision theory, the theory of multi-criteria and/or multi-objectives decision making and the theory of group decision making. Interested readers may refer to [38] for more in-depth discussions.

Applications exist to put such theories into practice especially in the growing area of multi-criteria group DSS. For example, the "Decider" system, a fuzzy multi-criteria group DSS [41], takes into account the nature of information which in reality is usually expressed in linguistic terms, and the hierarchic structure of the problem and the decision makers.

Other areas of application where group decision making is based on multiple criteria include new product development such as for garments [40] and digital scales [86] where preferences regarding the product have to be considered, and the car manufacturing industry where budget and time constraints are critical [35]. Another interesting application of DSS is to support a group of users in the choice of vacation packages [45]. Besides commercial applications, DSS are also found in areas that require long-term planning for sustainable development, for example, energy policy planning [62] and forest management [52].

Similar to the system established by Lu et al. [39] where fuzzy numbers are used to handle the uncertainties in the role of decision makers and the criteria used to arrive at the solution, a recent system in [59] uses fuzzy logic to construct a clinical DSS based on information input in the form of probability distributions. The unique aspect of this system is that the outcome given is not the single most desired solution, but rather, a set of solutions. By expressing the conclusion in this way, patients are more likely to accept the diagnostic decision from the health practitioner [23] (Table 1).

In terms of DSS for dentists, the information needed before the final treatment is decided will include the preferences of the patient in terms of cost and quality. For example, a fuzzy cognitive map is used to help the dentist decide on a suitable implant abutment for patients [34], combining expert knowledge from dentists and suppliers in the decision making process. Similarly, fuzzy logic is used by the system proposed by Ma et al. [42] to identify symptoms from patients, which are usually vague, making it difficult for the dentist to reach a detailed and definitive diagnosis.

Table 1
Recent decision support systems.

Systems	Comments
Selection of implant abutments [34]	Uses expert knowledge from dentists and abutment suppliers
Treatment of tooth fracture [42]	Uses fuzzy logic to help identify complaints from patients
Treatment of cavitated lesions [58]	Considers the patient's preference
Management of dental caries [4]	Considers the patient's oral history and health risk factors

Table 2
Major functionalities of clinical decision support systems adapted from [13].

Clinical DSS capabilities	Examples
Preventive care	Screening, immunisation and disease management suggestions
Diagnosis	Lists of ranked differential diagnoses
Treatment plans	Treatment guidelines and drug dosage recommendations

Another DSS described in [58] represents an attempt to personalise the treatment plan by considering patient preferences to reach a mutual agreement between the patient and the doctor. Although this is a positive move to attract more users to adopt decision support, it only focuses on treatment planning for a single treatment.

As dentists are limited by and differ in their cognitive functions, such as in the recall and application of possible risk factors, there can be potential differences in the decisions made by different dentists, or even by one dentist at different times. In order to minimise such divergence, the system proposed by Bessani et al. [4] considers expert domain knowledge and risk factors in decision support for caries management.

Though these systems utilise expert knowledge from dentists, there is no integration with a drug database which is essential within the clinical workflow.

The next section looks at some means of understanding DSS in terms of the technology underlying their designs, classifications and benefits they can bring to the dentist.

3. Understanding clinical decision support systems

A clinical DSS is an IS which has the ability to provide knowledge and personalised information to users, intelligently filtered to enhance health and healthcare outcomes [54]. They are not intended to replace the dentist's judgment and responsibility for decision-making, but to provide assistance in diagnosis and treatment planning [81]. Table 2 presents some system capabilities with examples. They can be general or targeted at specific situations such as implant placement, and the output can be delivered to the user either before, during or after the clinical decision is made [11]. The functionalities of DSS should follow the "five rights concept" [72] as a framework for planning and implementation:

- the right information (treatment planning, drug interactions);
- to the right people (dentists, patients);
- through the right channels (mobile devices, workstations);
- in the right intervention formats (alerts, graphics, info-buttons);
- at the right time within the clinical workflow (before drug prescription, at point-of-care).

This section outlines technologies underlying the design of a clinical DSS, various classification methods and the benefits they can bring to users if clinicians adopt them as a diagnostic tool at point-of-care.

3.1. Technologies

According to [17], a clinical DSS can be implemented as a passive system, a semi-active system or an active system according to how it is being triggered. Depending on the clinical tasks to be achieved, typical technologies used to develop such a system include machine learning, knowledge representation and data mining.

3.1.1. Machine learning

Machine learning is an appealing technique for its predictive ability based on existing representative data for diagnosis. Common machine learning techniques include Artificial Neural Network (ANN), logistic regression and support vector machines (SVM). ANN attempts to simulate the non-linear processing pattern of the human brain and is a very powerful tool for generalising acquired knowledge and data analysis by interweaving artificial neurons across input, hidden and output layers. For example, [56] used ANN for periodontal disease diagnosis and to classify patients according to their immune responses. ANN was also applied to support decisions on implant placements, where the system mimicked choices made by implant experts [65]. Though data learning and training in the hidden layer is not transparent to the user, ANN is simple to implement as it requires minimal statistical training. The logistic regression method utilises a simpler linear model, and unlike ANN which can handle arbitrary relationships between input and output variables, it can only be used if such relationships can be explicitly identified [2]. Thus, the logistic regression method is not as robust as ANN. To classify non-linear datasets for an effective diagnosis, SVM can be used, which separates complex datasets with a linear hyperplane. Due to the complex nature of the datasets, training time can be high, especially when the volume of the datasets is large. However, this can be reduced by excluding outlier data points. For example, [30] were able to obtain highly reliable drug failure prediction results with SVM when superfluous data points were excluded from the SVM ensemble construction.

3.1.2. Knowledge representation

Instead of learning from clinical knowledge as in machine learning, knowledge representation focuses on creating a knowledge description language which, when combined with a reasoner, is able to make diagnostic inferences. One approach in knowledge representation is the use of fuzzy logic, which is important in DSS as many applications deal with imprecise data and expect the results to have a dispositional rather than categorical validity. Unlike binary logic methods such as the above described ANN or SVM where the output is either true or false, fuzzy logic allows for different degrees of truth. In [42]'s design of a DSS for dental treatment, fuzzy logic was used to accept inaccurate and vague values of dental signs and symptoms associated with fractured teeth to produce possible treatment plans. Under rigorous testing conditions, the system was found to be similar to the dentist's professional predictions with respect to treatment for such situations.

Besides fuzzy logic, ontology-based systems can also be used to represent expert domain knowledge. [58] developed a shared DSS for dental fillings. An ontology was built based on tooth anatomy, diseases and treatment options. This enables ontology-generated evidence-based alternatives to be made available for dentists and patients to reach a shared decision on the most effective treatment plan.

Since use of radiographs feature prominently in oral disease diagnosis [71], information from the images should also be stored in the knowledge base. This focus on the problem rather than the technology corresponds to an improvement from the conventional method of diagnosis and meaningful use of DSS [36].

Table 3
Classification of clinical decision support systems.

[14]	[32]	Proposed method
Simple: interactive query Complex: prediction of diseases using ANN	Basic: checking on drug interactions Advanced: individualised dosing support	Static: EHR, appointment reminders, drug allergy alerts Dynamic: knowledge base integration, self-learning

3.1.3. Data mining

For unstructured data, text mining techniques can be used to discover context-specific knowledge based on patient-specific profile in supporting dentists in their decision-making process for a specific oral health situation.

Semantic meanings can be extracted from textual data through data mining methods based on rules created from concepts and relationships within the appropriate ontology. [85] used a data mining method to identify relationships between medications for diabetes patients. By identifying patterns within the drug database, the system was able to predict, with significant accuracy, the subsequent medication to be prescribed.

3.2. Classification of clinical decision support systems

In the literature, there are many ways to classify DSS, according to their features and functions. For example, as shown in Table 3, [14] classifies them according to complexity of the systems functions. A simple system is one that accepts a command from the user and produces a response to the user. As an illustration, the user may use the system to check for drug reactions to a particular drug by entering the drug name, and the system then displays the results to the user. Complex systems use a “black-box” approach, including artificial intelligence, logistic regression and data mining, to produce advice or diagnostic predictions to the user. Examples include systems for identification of prostate cancer, sleep apnoea and psychiatric problems. Unfortunately, there are no examples in the area of dental pathology. This is expected as even in the medical domain, complex systems are difficult to customise to local clinical workflow, not to mention being difficult to develop as it requires both design expertise from the researchers and relevant knowledge from the users within their clinical domain [14].

Similarly, [32] refers to systems that perform checking on drug-drug interactions as basic systems. Those with more elaborate features such as checking on contra-indications and dosage support are referred to as advanced systems.

In the context of DSS for dental clinics, it is recommended that such systems be classified as static and dynamic to reflect the approach taken in the design and implementation of the system within the clinical workflow. Static systems are those which do not possess the learning ability that dynamic systems can provide to the dentist. With machine learning features incorporated into the design, dynamic systems are able to provide real-time personalised support to the dentist where the medical profile of each individual patient is taken into consideration.

According to these definitions, the systems that correspond to the simple or basic groups of DSS referred to earlier will be known as static systems since such systems are not personalised to the individual patient. Systems that provide logistic and administration support also come under this category. Examples are programs that allow storing, searching and retrieval of information on the clinic’s inventory, accounting and patient information.

On the other hand, dynamic systems are designed to incorporate reasoning and self-learning capabilities so as to provide personalised support at point-of-care to the dentist within the clinical workflow. One critical feature in personalised support is in the area of drug prescription, where the system should be able to support the dentist in determining if the drug to be prescribed is safe for the patient by considering the individual’s relevant medical history - the drugs the patient is currently taking, the drugs the patient is allergic to, and the medical conditions of the patient [21].

Hence, dynamic systems typically incorporate a drug knowledge base to store decisions made by the dentist and information on side effects and interactions of drugs. It is crucial in a dynamic system to ensure that the drug knowledge base is updated regularly, not only with the latest information on drugs, but also with the decisions made by the dentist. This will allow the system to capture the ground truths from the dentist and in turn, become more efficient in providing relevant information.

Following the suggested approach in the classification of DSS, if the system is not self-learning, it will be grouped as static even if it provides advanced features such as the dosing support mentioned in [32]. On the other hand, a system that provides answers to simple queries [14] or basic functions [32] on drug interactions can be considered a dynamic system if such queries take into account the relevant medical history of the individual patient and is able to learn from previous decisions of the dentist.

3.3. Benefits of decision support systems

Besides assisting dentists to make timely and informed treatment decisions, a DSS is also useful in the following areas [50,83]:

- keeping electronic health records (EHR);
- drug prescription, medication dosing support;
- clinical reference count;
- point-of-care alerts and reminders.

In addition, a well-designed system which integrates patients’ EHR will complement evidence-based decision making for the dentist with benefits that includes less paperwork, better tracking of data, accounting and reporting functionality [7]. Storing the daily clinical decisions and treatment outcomes will enable the system to “learn” and possess more knowledge to solve subsequent clinical problems. With datasets stored in ontology and made available using the techniques and technologies of the Semantic Web, the data will become accessible for further data analysis and knowledge discovery. This produces a platform that supports a “range of scientific research activities intended to advance our understanding of dental conditions and the relative success of different treatment interventions” [73]. Consistent and reliable information will also avoid misdiagnosis and malpractice, which can lead to expensive legal suits. With comprehensive drug information and diagnostic support provided in real-time at point-of-care within the clinical workflow, there will be improved clinical efficiency, oral health outcomes for patients and job satisfaction for the whole dental team.

3.4. Summary

This section outlined approaches in understanding DSS in terms of the technology underlying their design, classifications and benefits to the user. As summarised in Fig. 2, the right technology behind the design of DSS will ensure the system is self-learning and has the most recent and relevant information on the patient’s

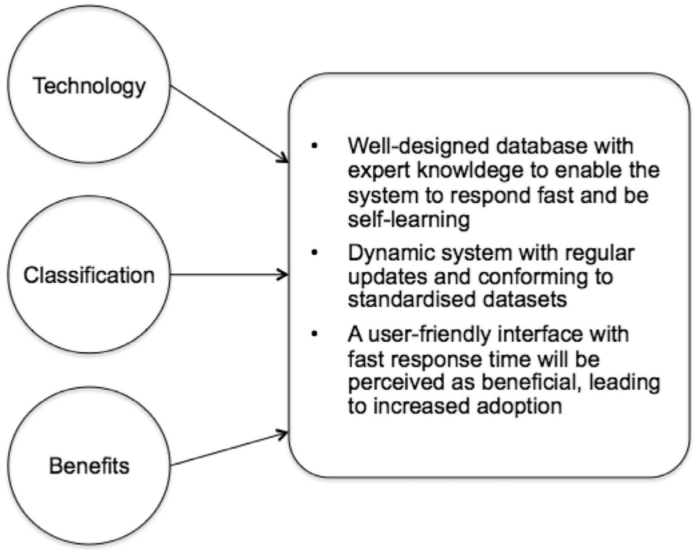

Fig. 2. Ways of understanding decision support systems.

medical conditions and drug allergies. Besides providing static information, it should be dynamic where the knowledge base is updated regularly and able to give alternative suggestions based on the personalised medical status of the patient. A dynamic DSS will be perceived as beneficial which results in increased adoption by users within the clinical workflow. Hence, it is important for clinical DSS to be able to progressively learn from the user's decisions and make diagnostic personalised inferences in a user-friendly manner.

Despite the benefits that a DSS can potentially bring to the user as described in this section, many dentists are still not adopting it as a diagnostic tool in their daily practice. The next section looks at the common barriers that hinder such an adoption.

4. Barriers to adoption of decision support systems

Although DSS have existed since the 1990s, adoption in the clinical workflow is still poor. This section looks at some of the major barriers to DSS adoption and implementation as a treatment planning tool by dentists.

4.1. Lack of perceived usefulness

As mentioned in Section 3.1.2, the focus of diagnosis should be on the problem and not on the technology [36]. Many dentists feel that they can diagnose the problem better than the DSS, perceiving that such systems are not useful within their clinical workflow. Poor usability is often cited as a reason for slow adoption of IS as it "makes it difficult for providers to navigate through the information and obtain an integrated view of patient data" [76]. Besides, most systems only support a particular kind of treatment, such as treatment planning for dental caries [42,57] or the selection of implant abutments [34].

Such limited scope also contributes to their slow adoption rate [73]. A qualitative case study in [70] with thirty-seven doctors found that usefulness in relation to consultation issues is one of the driving factors for adoption of DSS in diagnosing clinical problems. Though it investigated medical doctors, the findings can be applied to dentists as well, with other studies also supporting this conclusion. For example, [80]'s findings are in agreement with the Technology Acceptance Model [10] which posits perceived usefulness as a determinant in usage intention of technology.

In another study which uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model to categorise barriers to clinical DSS adoption, performance expectancy (which includes perceived usefulness), defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" [80], is again the strongest predictor of usage intention. A literature review conducted in [12] has identified barriers to performance expectancy of DSS, with the top five being:

- time constraints;
- obscure workflow issues;
- authenticity/reliability of information;
- disagreement with the system;
- interoperability/standards.

A study on how clinicians diagnose and treatment plan also reveals that sources of information used by dentists come as separate blocks which distracts the users and has adverse effects on efficiency [76].

4.2. Complex sociocultural and economic factors

Dentists envisage that a DSS is not very useful in aiding diagnosis, and they are used to depending on their own clinical skills or at most a quick discussion with colleagues before arriving at a treatment plan. Medical practitioners are used to the culture of autonomy, and using such a system will disrupt that autonomy leading to resistance to their adoption within the clinical workflow [79]. A study on perceived barriers for a group of rheumatologists discovered a sense of ambivalence relating to concerns that using technology could impair doctor-patient communication [88]. Many studies have also noted that practitioners are reluctant to use the system in front of patients [12]. This is expected since practitioners do not wish to be perceived as lacking in diagnostic skills or appear to be inefficient in navigating the system. Resistance to new technology is not just confined to DSS, as can be seen from the introduction of the blood pressure monitor into the clinical workflow during the early 20th century. At that time, physicians deemed that their unique skill in taking blood pressure by palpation was being challenged and thus felt uneasy about using such technology [9]. However, it is so common nowadays, to the point that it has become a do-it-yourself gadget and can be used by anyone at home.

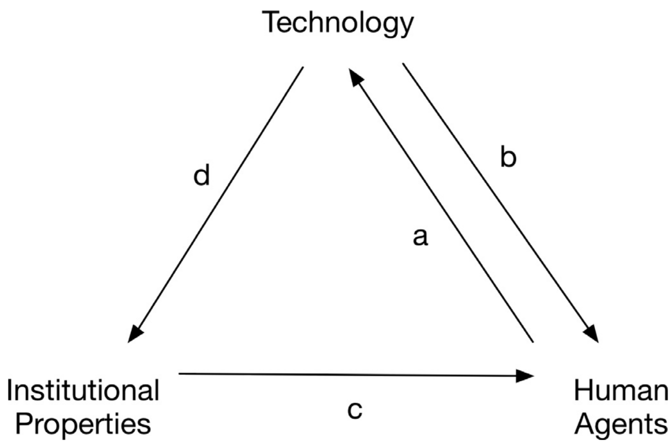

Fig. 3. Structurational model of technology, adapted from [53].

In [43], a study to understand the lag in IS adoption, discovered that financial gain and time savings are crucial factors in influencing technology adoption, suggesting that for a clinical DSS to be used at point-of-care, a fast response time is required.

Research by Mamatela [44] with African doctors identified environmental factors to contribute to the practitioner's propensity to adopt the use of electronic health technology. [78] also discovered that the diffusion rate of a new technology depends on social influence from peers and the perceived advantage the system will bring about to their workflow.

Horgan et al. [26] performed a comprehensive survey of why personalised medicine is not being accepted by many clinical establishments, and found important factors to include differences in company cultures and the practitioner's ability to use and interpret results from the IS.

Ovretveit's et al. [55] exploration of the barriers impeding the adoption of IS in a clinical environment at Stockholms Karolinska University discovered that consultation before implementation is a prominent factor in successful implementation of an IS, and that the perceived usefulness of the new system aligns with Roger's Theory [61]. While most studies focus on the economic aspect of technology [49], this study looks at barriers to adoption from the sociocultural aspect.

The findings also appear to support the theoretical model from [53] which explains how the way that users (i.e., dentists, dental assistants) interact with technology is influenced by the corporate culture within the clinic. The model is an attempt to explain that technology is a product of human design and yet used by humans to accomplish the designed task. As illustrated by the model in Fig. 3, such actions are very often confounded by the social environment of the work place.

A study in [51] also strongly suggests that socio-technical connectives between users and technology should be considered when developing electronic health systems.

4.3. Difficulties in interpretability

Interpretability, in terms of interfacing and standards, is another issue that has the potential to influence DSS adoption.

4.3.1. Human computer interface

Usability and human factors being the first recommended domain within the research agenda tasked by the American Medical Informatics Association [46] highlights the significance of user interface in DSS. Without a well designed interface, the personalised and smart learning features of the IS will not be fully utilised and its usefulness will not be perceived by the user. In fact, user-friendliness is important in increasing the "usability" of the system as it will make it easier for the dentist to navigate and obtain an integrated view of the patient's data [76].

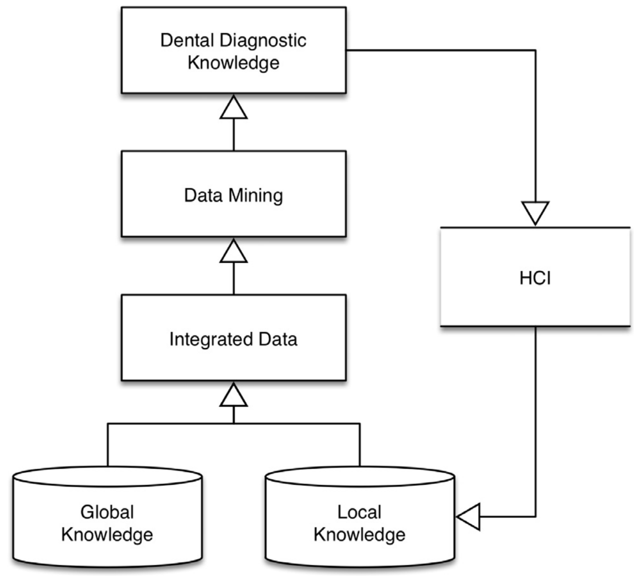

Fig. 4. Role of HCI in an iIntelligent information system.

As shown in Fig. 4, the human computer interface (HCI) plays an important role within the cyclic path of the local expert knowledge base and diagnostic result from the DSS. An effective system will have a user-friendly interface to enable the dentist to understand the given result from the system. Based on the result, the dentist will be able to further update the local knowledge base. With the updated knowledge base and data mining techniques, the system will be able to continue to produce useful and relevant information for the dentist to make subsequent decisions. A smooth and efficient human-computer integration such that knowledge can be obtained with ease will result in more clinicians accepting and using the technology [18].

As an efficient and effective IS involves communication between the system and the user, a comprehensive interface design is crucial for the successful construction and flow of an appropriate knowledge base. [77] observed that there is little research on the application of cognitive engineering methods to support system design. More studies are required to observe how dentists interact with patients and computers as the results will contribute to the design of an IS that can enhance cognitive support for dentists [76].

4.3.2. Lack of standards

Lack of standards and lack of time act as barriers to clinical DSS adoption [12]. While a DSS needs to simulate the decision-making process of the dentist, the result of the process may appear difficult to interpret for the dentist due to emerging standards of healthcare information technology [14], and may cause dentists to spend too much time on the system during point-of-care. Since good design of a system requires the efficient collaboration of knowledge from patient profiles and other knowledge bases, standardisation of data is important to ensure the system performs efficiently.

4.4. Summary

This section has identified perceived usefulness as one of the main barriers against DSS adoption by dentists. Other barriers as

Table 4
Barriers to adopting decision support systems.

Barriers	Remarks
Perceived usefulness	Limited functions
Sociocultural and economic factors	Resistance towards technology
	Social and corporate influences
User interface and standards	Lack of standards for datasets
	Difficult to interpret results

Table 5
Current and expected fFeatures of clinical decision support systems.

Current Clinical DSS Design Features	Expected Design Features
Separate display of information sources [76]	Integrate medical and dental history [63,68]
Simple, static and non-learning [14]	Intelligent and personalised [26]
Perceived as not useful and time consuming	Efficient searching, retrieval algorithm and user-friendly HCI
Limited scope [73]	Interoperability and accessibility [19]

indicated in Table 4 include various complex sociocultural factors, system interface and the issue of standards.

As perceived usefulness also implies a system with an acceptable response time and a user-friendly interface, many users are reluctant to use clinical DSS as current systems have limited functions and features, are perceived to be difficult to use, and require unwarranted effort to interpret the results produced by the system.

A lack of concern for the user's needs and expectations contributes further to the lack of propensity to adopt the system within their clinical workflow. Perceived advantages that the system will bring about, such as possible time savings within the user's workflow (thus leading to cost savings), are also crucial factors in influencing technology adoption by the dentist.

The next section surveys some of the current DSS that attempt to overcome these barriers.

5. How decision support systems overcome barriers

The need for a robust and intelligent self-learning system has been identified by IBM as one of the challenges in effective healthcare delivery [1]. Such a system should have appropriate tools and techniques to provide decision support to users [74]. Most current systems consist of only simple alerts and reminders with no sophisticated advisory functions [14]. Table 5 presents some features available in the design of current DSS, in comparison with the features expected to appear in future systems as suggested by some researchers.

The following sections highlight some of the important features in these systems that attempt to minimise the barriers to the dentist's adoption of clinical DSS.

5.1. Efficient design of knowledge base

It appears that many designs contain a knowledge base of rules pertaining to the expert knowledge of the application. For example, for an application that targets implants, [87] described a dental expert system, which stores facts on symptoms and diseases with static general information of patient profiles to assist the dentist in disease diagnosis. It stresses the importance of an evidence-based diagnostic approach instead of an experimental one and provides a modular design framework containing a knowledge acquisition database, a general database, an inference engine and the user interface. The knowledge acquisition database is important for any DSS to be useful for the users, and is critical in assisting the dentist to make an intelligent treatment plan [48].

Similarly, [34] has researched the optimal selection of dental implant abutments. A fuzzy cognitive map is used to contain rules and expert domain knowledge from both the dentist using the system as well as domain experts from implant manufacturers. To enhance patient satisfaction and effective treatment, the clinical DSS not only stores expert knowledge but also generates treatment options using ontology that contains the patient's profile and their preference of options [58].

Mago et al. [42] also developed a system to reduce inconsistencies in treatment planning for a fractured tooth. Fuzzy logic, first introduced in [75], was used for its strength in dealing with imprecision pertaining to dental disease and symptoms.

In another clinical DSS described in [57], anatomy and diseases are stored in a database according to standards from FMA and ICD-10 respectively. By linking treatment with information from the database, the system was able to aid the dentist in treatment planning and reduce the need to primarily rely on memory of similar cases, or by trial and error.

As seen from the design of current DSS, the knowledge base plays an important role in providing treatment options to the users. Naturally, such domain knowledge needs to be regularly updated, otherwise the options provided will be based on outdated knowledge and irrelevant. With the help of the Delphi technique in a six-month study at King Faisal Specialist Hospital and Research Center to collect experiences and suggestions on strategies for successful implementation of decision support, it was reported that the need to update these knowledge bases is one of the success factors for a clinical DSS to be useful and gain user acceptance [32]. To allow such knowledge bases to be reviewed, updated and managed effectively, an important feature in current systems is to ensure that these clinical rules and knowledge be separated from the main IS application. This leads to cheaper service integration of DSS into existing IS [33] and also enables such systems to utilise information from local knowledge base with those from other ontology. Fig. 5 is an illustration of the model.

Though the current clinical DSS utilise knowledge bases in their design, they are of a limited nature, restricted to a particular kind of treatment plan. Even if it is focused on diagnosis of a common disease such as dental caries, the knowledge base is not self-learning. For example, the DSS developed by Park et al. [58] for dental fillings needs to be expanded to include clinical guidelines from global dental ontology in a real-time manner and integrated with local knowledge, in order for the system to be self-learning and to allow practise of evidence-based dentistry. This involves semantic annotation that requires complex machine learning techniques [73]. Since dental ontology can enable DSS to automatically update their knowledge base with expensive expert medical and dental knowledge, it will be easier and cheaper to maintain the clinical DSS with the current expertise of dentists and the latest existing knowledge in scientific and clinical evidence [73]. Additionally, the efforts of researchers and dentists can be harnessed easily through a Semantic Web interface provided by dental ontologies which act as a consensual representation of knowledge in the dental domain [73]. Good design and fast response time will increase the appeal of such a system.

5.2. Ontology

We expect that a DSS is not only efficient enough to appear helpful to dentists, but also to fit the clinical workflow at point-of-care, which commonly requires it to handle multiple diseases and drug allergy information. [5] designed a clinical DSS to produce a treatment plan for dental caries. Based on the different degree of oral symptoms, the system suggests possible treatment plans based on the Bayesian Network. Another system in [4] also used the Bayesian Network as an inference engine to produce

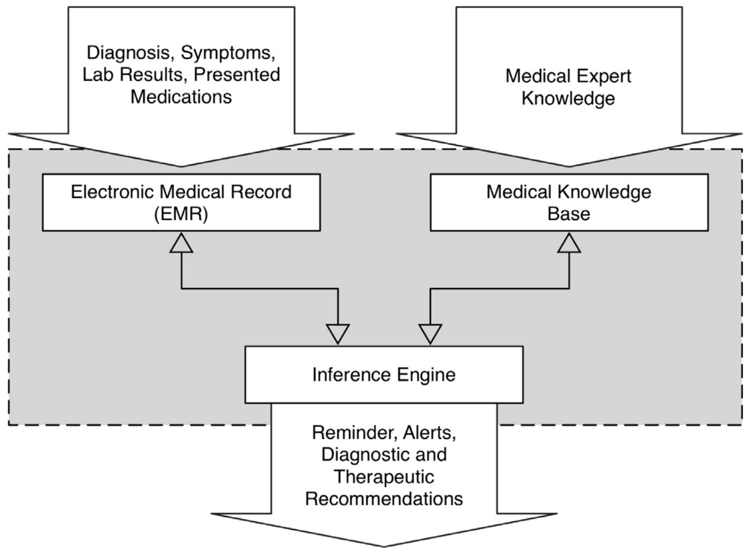

Fig. 5. Clinical DSS model adapted from [15].

treatment options based on patients' oral health history and risk factors. Though these systems help the dentist to treat the patients more confidently, they are only restricted to situations involving dental caries. Furthermore, there is no interfacing with ontology knowledge based on dental disease and drug information.

The inclusion of drug ontology is important as drug information is commonly needed within the clinical workflow and is a basic point-of-care activity in oral health therapy. In a study by Devaraj et al. [12], over half the literature short-listed for review utilise patient disease in their DSS. This reflects that patient disease/condition management is the area where physicians require most assistance in decision-making. Therefore, a clinical DSS which integrates with drug knowledge bases to advise on drug suitability before prescription will appear helpful to dentists and overcome the performance expectancy barrier.

Ontology should be updated in real time without the need for manual intervention. Using this technology also requires the standardisation of datasets, with the need to only be familiar with one set of terminology increasing the attractiveness of usage.

5.3. Human computer interface

As described in Section 4.3.1, a poorly designed user interface downgrades the performance and reduces the benefits to clinicians [27], resulting in a barrier against system adoption. A well designed interface enhances usability and cognitive support for the user to make better and faster decisions. The system proposed by Park et al. [58] also integrates expert knowledge from the patient and existing ontology though it is unclear if the ontology is updated in real-time. Overall, it is a good system except for the lack of a drug checking function, which is essential within the clinical workflow.

Many existing systems lack the usability and friendliness that users expect from an IS. In a survey on factors influencing implementation and outcomes of a dental recording system, less than a third of the respondents ($n = 130$) thought that the system improved productivity when asked: *"What do you like about the Electronic Patient Record System?"* The majority favoured its increase of legibility and improved access to patient charts [82]. The results suggest a need to enhance the usability of IS. In order to transform patient profiles and data in a knowledge base into useable and useful knowledge, a user-friendly HCI, perhaps with natural language processing capability, must be designed with a cross-disciplinary

Table 6
Overcoming barriers.

Features	Remarks
Effective design of database	Insightful use of expert knowledge
Ontology	Important to link to drug and disease knowledge bases
User-friendly interface	Overcome the performance expectancy barrier

framework in mind to combine the cognitive and reasoning ability of the expert user and the fast and accurate data mining processing power of the IS [25]. A good interface is also crucial in the technology diffusion process to enable high acceptance and absorption rates.

As aforementioned, radiographs are useful diagnostic tools for the dentist to identify oral diseases. [60] described a caries detection system to assist the dentist in making accurate and timely decisions on diagnosis and treatment planning. As illustrated in Fig. 6, the original image is enhanced to enable the user to more accurately identify the exact location of the caries. The image is then segmented to eliminate misjudgment, and feature extraction performed to enable the algorithm to identify the location of the lesion for the dentist to make further judgment on the treatment plan.

ORAD (Oral Radiographic Differential Diagnosis) is a system developed by White [84] to identify intra-bony lesions from radiographs to produce a list of possible diseases. It was found that the system is useful as an adjunct for the dentist in diagnosing oral diseases [71]. As can be seen from current systems, there is yet an ideal design to cater for real-time updating of ontology and treatment planning for multiple oral therapies as well as drug information checking before prescription at point-of-care.

5.4. Summary

This survey explores key features that are crucial for the adoption of DSS by dentists, such as effective design and a user-friendly interface. To help dentists overcome adoption barriers, systems should be well designed to enable the user to make effective and efficient treatment plans without having to depend on memory of past cases. As indicated in Table 6, systems which incorporate visual representations in identifying oral disease with

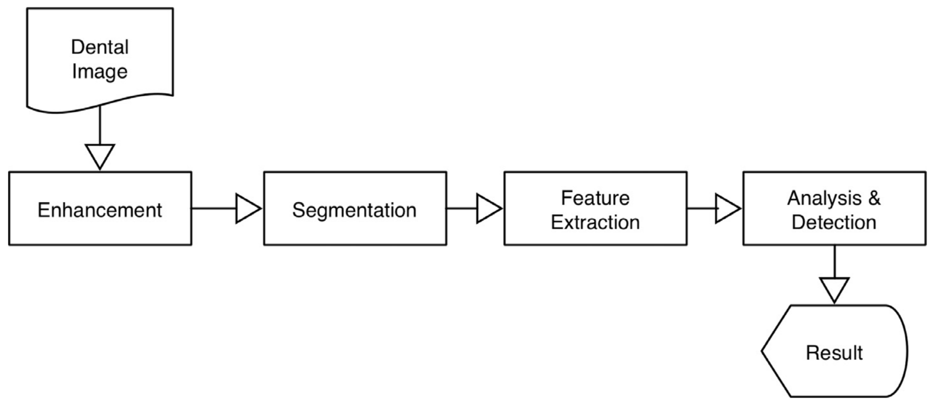

Fig. 6. Dental caries detection algorithm framework adapted from [60].

user-friendly interface will help the dentist overcome the performance expectancy barrier.

A survey of existing DSS with features that support treatment planning for the dentist found that such systems offer treatment options only for a single aspect such as selection of implant abutments or the identification of dental caries.

Systems that are personalised to the patient's oral health profile with a user-friendly interface will be perceived by dentist as more useful. This will help them to overcome barriers in their decision to adopt a DSS within their clinical workflow. Even within such a personalised system, there is still a lack in real-time interfacing with drug and disease knowledge bases to enable treatment planning for multiple oral therapies and recommendations in drug prescription.

6. Trends for clinical decision support systems

Research and development on DSS should continuously keep pace with technology changes so that the system can fit the diagnostic requirements of users and be adopted into the clinical workflow. This section highlights some of the emerging trends such as the use of big data in personalised systems - recently mentioned as a top contribution in a survey of 1254 papers published in 2014 in the field of clinical decision support [6] - as well as the issue of privacy.

6.1. Big data

With an ever-increasing volume and type of knowledge to be stored in an IS (for example, structured, semi-structured and/or unstructured), it remains a challenge for the system to allow processing and searching techniques to interact efficiently with human intelligence. Compared to other fields such as education and finance, velocity and variety of data generated in healthcare is much more significant, with Fig. 7 illustrating a big data heat map covering these domains, adapted from [68].

From the heat map, it is evident that the quantity and expected speed of processing, analysing and distributing of information in healthcare will "bring the potential to discover new knowledge that can improve work practices and produce better outcomes" [68]. This is particularly true in the dental clinic where the dentist needs to consider information from intra-oral images, 3D images, unstructured clinical notes and the patient's profile in real-time at point-of-care before deciding on a personalised treatment plan.

Big data, which integrates knowledge through analytic tools such as Semantic Web, offers advisory functions such as personalised treatment options, in addition to the typical administrative functions. Furthermore, the indexing of clinical and non-clinical datasets of big data will help researchers discover new knowledge and relationships among multiple variables, which is impossible with unconnected and disparate data sets.

Hence, design and implementation of clinical DSS should exploit the notable potential of big data. The system should effectively and efficiently analyse, integrate and interpret knowledge to be used by the user in enhancing treatment outcomes and patient health [25]. Due to information silos, which fragment the medical and dental domains [69], it is important that data from both domains is seamlessly integrated for efficient processing and distribution to clinicians. Besides early medical prognosis (as many medical conditions are manifested first in oral cavity), other benefits of medical and dental record integration are [63]:

- improved decision-making;
- improved patient outcomes through prevention, early detection, and proper intervention;
- transparent information across medical and dental providers;
- reduced cost to providers.

In addition to the challenge of information silos in knowledge bases is the need for DSS to be able to reference and reason from these databases to produce an effective personalised treatment plan. For example, by using OWL 2 (an ontology language for the web), [57] designed a system to generate dental treatment options by querying knowledge bases that represent the type of disease and tooth location. Datasets containing drug information will also be very useful for the dentist when prescribing drugs at point-of-care. This is to allow dentists to ensure that the patient will not suffer from an adverse effect from a cross-allergy to the prescribed drug (usually due to similarities to a drug that the patient is know to be allergic to) or an interaction between the prescribed drug and the drugs that the patient is currently taking.

6.2. Personalised systems

Among the many knowledge domains to be stored in a typical clinical DSS, there is a growing interest in the field of genomics to cater to genetic variations among patients. Focusing on such personalised information will result in greater quality of care and reduced healthcare cost, so it is not surprising that pharmacogenomics, the use of patient genotypes to explain individual differences in drug responses [29], is one of the most common examples of personalised medicine [26]. [20] predict that personalised medicine will replace the traditional trial and error approach in healthcare. More specifically in oral healthcare, [19] argues that personalised medicine based on the individual's unique genetic, molecular and clinical profile should be the aim for researchers and dental practitioners in providing quality, customised and effective healthcare. [16] anticipates that applying genomic information

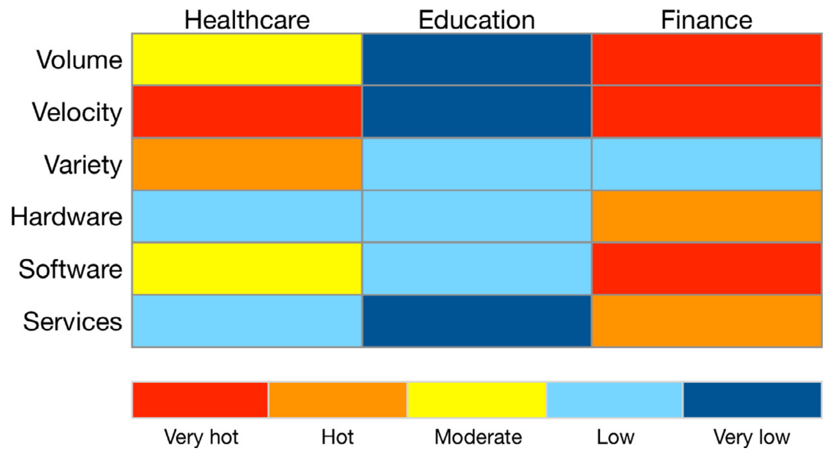

Fig. 7. Big data heat map adapted from [68].

to oral disease diagnosis will allow a better understanding of disease aetiology, leading to preventive measures being implemented prior to disease onset.

A recent proposal by Welch et al. [83] for a framework to support DSS using genome sequencing predicted that a DSS provides the greatest opportunity to enable the use of genetically-guided personalised medicine. Hopefully, the collaboration between eMERGE [22] and [8] will lead to a standard for genome-informed IS and fulfil the vision for personalised medicine in the near future.

Hence, it is important that potential systems are personalised to the patient's profile to align with the trend towards personalised medicine.

6.3. Standards and privacy issues

As discussed in Section 4, interoperability and standards are one of the top barriers in adopting DSS. The difference in data formats from different vendors and countries not only reduces interoperability but also makes the merging of complex data sets complicated [26]. Thus, the challenge is to standardise the knowledge base format to enable the system to reuse and reason data in the knowledge repositories. In fact, focusing on a standard approach to knowledge sharing is one of the most active areas in current research in translating support from campus research to clinical point-of-care [47]. To ease practical development of DSS, design should endeavour to conform to standards such as [24] with clinical terminologies adhering to interoperability specifications such as those owned and distributed by the [28]. This will remove another barrier against adoption of a clinical DSS. While it is important to unite and standardise different data and coding standards, there may be potential issues of privacy with regards to patient information. For dentists to adopt and integrate DSS, there is a need to convey both to patients and practitioners that secure protection of information is in place within the system. Privacy regulations are required to balance against the need for exposure of data between researchers and developers [1].

In summary, with the ever-increasing volume of data appearing in different genres and formats, clinical DSS should be capable of integrating them and making inferences to effectively process and produce clinically relevant knowledge to support decision-making by dentists. The challenge of information silos requires systems to work on standardised datasets stored in an ontology which can be inferred and retrieved through the latest Semantic Web technology. While research efforts are focusing on maintaining a uniform knowledge base format for effective sharing and reasoning, the delicate issue of privacy needs to be addressed carefully so that personalised features of a clinical DSS can be fully utilised by dentists without the risk of compromising the confidentiality of their patients' information.

7. Conclusions

This paper presents a survey on clinical DSS for adoption in dental clinics, pushing for the need of a personalised system so that dentists can provide a more efficient treatment outcome at point-of-care within their daily clinical workflow.

Although DSS can be helpful to the dentist, this survey has identified major barriers to adoption of such technology, such as perceived usefulness and social factors, as well as some of the key features in current systems that attempt to overcome these barriers.

In order to gain acceptance, it is recommended that a personalised clinical DSS be designed to offer treatment planning as well as alerts and advice on drug prescription, since disease management is a priority for dentists and thus warrant assistance from such a system. To achieve this requirement, local knowledge from the dentist and patient profile should be able to be integrated with global ontology in the medical and dental domain.

This survey is a step forward in understanding the barriers against the adoption of a clinical DSS with particular focus in the context of a dental clinic, and has highlighted critical features required for such systems to be readily adopted by the dentist within their routine clinical workflow at point-of-care.

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