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Artificial intelligence to support early diagnosis of temporomandibular disorders: A preliminary case study

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Abstract

Background: Temporomandibular disorders (TMDs) are disabling conditions with a negative impact on the quality of life. Their diagnosis is a complex and multi-factorial process that should be conducted by experienced professionals, and most TMDs remain often undetected. Increasing the awareness of un-experienced dentists and supporting the early TMD recognition may help reduce this gap. Artificial intelligence (AI) allowing both to process natural language and to manage large knowledge bases could support the diagnostic process.

Objective: In this work, we present the experience of an AI-based system for supporting non-expert dentists in early TMD recognition.

Methods: The system was based on commercially available AI services. The prototype development involved a preliminary domain analysis and relevant literature identification, the implementation of the core cognitive computing services, the web interface and preliminary testing. Performance evaluation included a retrospective review of seven available clinical cases, together with the involvement of expert professionals for usability testing.

Results: The system comprises one module providing possible diagnoses according to a list of symptoms, and a second one represented by a question and answer tool, based on natural language. We found that, even when using commercial services, the training guided by experts is a key factor and that, despite the generally positive feedback, the application's best target is untrained professionals.

Conclusion: We provided a preliminary proof of concept of the feasibility of implementing an AI-based system aimed to support non-specialists in the early identification of TMDs, possibly allowing a faster and more frequent referral to second-level medical centres. Our results showed that AI is a useful tool to improve TMD detection by facilitating a primary diagnosis.

KEYWORDS
artificial intelligence, cognitive computing, decision support system, early diagnosis, temporomandibular disorders

1 | INTRODUCTION

Temporomandibular disorders (TMDs) are a group of clinical conditions that may cause pain and dysfunction in the temporomandibular joint (TMJ) and in the masticatory muscle that controls jaw movements.[1,2] Individuals with TMD may show a limited range of TMJ movements, or they may experience sounds during movements involving the TMJ, such as chewing or speaking.[3] Pain intensity and depression levels associated with TMD are similar to those reported for other chronic pain conditions.[4] TMDs, therefore, represent a disabling condition, with a negative impact on quality of life.[5]

Temporomandibular disorder diagnosis, mostly guided by an international consensus between experts (diagnostic criteria for TMD, DC/TMD[2]), involves a multi-factorial evaluation of the patient spanning from an objective evaluation of mandibular motion range to clinical and psychological questionnaires and diagnostic imaging. This complexity is accompanied by the need for experienced professionals and a possible increase in diagnostic errors.[6] In addition, there is evidence suggesting that these disorders are largely undetected, even though the reasons behind this are still unclear.[5] A hypothesis could be the lack of appropriate training in undergraduate educational programs[7] that impacts the ability of young and un-experienced dentists to identify TMDs.

In our big data era, artificial intelligence (AI) and specifically machine learning (ML) techniques, used to extract, combine and understand hidden information,[8] are regarded as ways to improve the diagnostic process of TMDs.[9] In fact, in the last 2 years, ML-AI techniques, which are extensively used in healthcare, faced an increasing adoption also in dentistry,[9] and more specifically in TMD diagnosis.[10–14]

As ML requires large datasets for appropriate training, the literature mostly reports the use of automated techniques for the interpretation of bioimages, mostly Computerised Tomography (CT) or Magnetic Resonance Imaging scans.[10–15] These are used in TMD diagnosis as quantitative tools to appropriately classify the type of disk displacement, with high accuracy. Other types of imaging, such as infrared thermography[11] or cameras for the detection of biomechanical facial features[6] analysed through ML, showed encouraging results.

Apart from the use of ML techniques to evaluate risk factors associated with the occurrence of TMDs,[16] there have been very few attempts to address the diagnostic process starting from the patient's symptoms and DC/TMD. In 2018, Nam and colleagues,[17] used text mining and natural language processing to infer the different language used by TMD-mimicking patients as compared to TMD-genuine patients, thus supporting the differential diagnosis. In an earlier attempt in 2012, artificial neural networks were applied to classify the TMD subgroup from the reported symptoms.[18] The authors found heterogeneous sensitivities/specificities in the classification of different subgroups, with the lowest sensitivity associated with bilateral anterior disc displacement without reduction, and the highest with bilateral anterior disc displacement with reduction. However, the authors concluded that such an approach could be useful to support dental practitioners.

Building on these previous experiences, we propose an architecture and proof-of-concept testing of an AI-based system to support untrained dentists in recognising TMDs in their patients, thus referring them to expert professionals in early phases, and with the suggestion of appropriate diagnostic testing as indicated by DC/TMD. The system comprises two main modules, one able to provide a list of possible diagnoses, with probability ranking, according to a list of symptoms observed on/reported by the patient (decision support module), and the other one being a question & answer tool, based on natural language, used by the inexperienced clinician to retrieve relevant and scientifically sound answers on TMDs (educational module).

2 | METHODS

The implementation was based on commercially available cognitive computing services, trained using scientific documents and interviews of expert professionals (with at least 10 years of experience in oro-facial pain) regarding the diagnosis of TMDs. The prototype development involved a preliminary domain analysis, aimed to identify the most relevant literature needed for system training, the implementation of the core cognitive computing services, the development of a web interface and proof-of-concept testing.

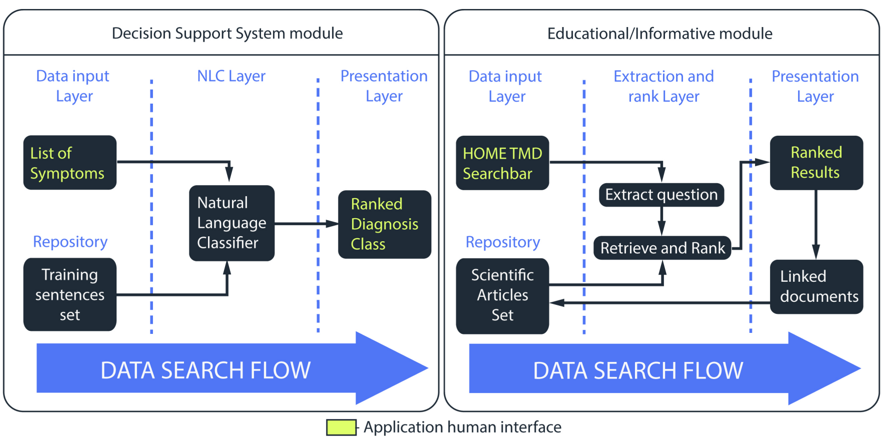

FIGURE 1 System architecture for the decision support system module and the education/informative module. NLC, Natural Language Classifier.

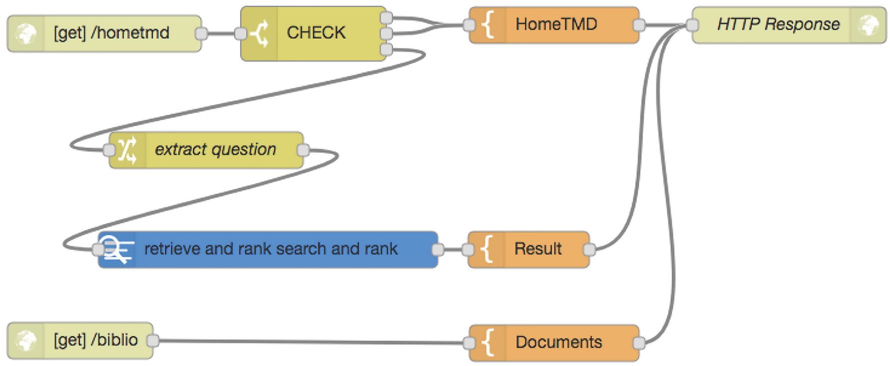

FIGURE 2 Node-RED schema for retrieving and rank search of the Informative/Educational module.

The general architecture of the system is shown in Figure 1. The two modules, namely the decision support module and the educational/informative module, are implemented using commercially available services on the IBM Cloud platform, namely the IBM Watson Natural Language Classifier and the IBM Watson Retrieve & Rank. The user interface collects the practitioner's inputs and calls the appropriate service to provide the answer.

2.1 | Domain analysis

The DC/TMD criteria[2] and their cited literature were considered the most relevant source. To them, we added information sources coming from the Medline Plus service of the National Library of Medicine of the National Institutes of Health (NLM-NIH), to add a reliable source with a non-specialist language, and other information coming from the National Institute of Dental and Craniofacial Research. Of note, we decided to select only English sources, to avoid translations, thus possibly optimising the responses, even though we worked in an Italian language environment. All the clinical terminology used by all the involved personnel was standardised English (SNOMED-CT Core compliant), also the user interface language was American English. We also interviewed clinical TMD experts from the Clinica Maxillo Facciale e Odontostomatologica of the Ospedale Maggiore in Trieste and the University of Trieste and from the Department of Surgical Pathology, Medicine, Molecular and Critical Area of the University of Pisa to obtain other relevant inputs.

2.2 | Cognitive computing services

In this first prototype, we decided to use available commercial services provided by IBM Watson, even though this choice may be changed in future releases, especially to provide systems working not as prototypes but as real services. In fact, advanced deep learning (DL) algorithms require extensive computational power and a fast Internet connection to gather data from the various online repositories and it is seldom available on a simple clinician's laptop. Through commercial services, it is possible to delegate these requirements remotely. However, this approach comes with the clear disadvantage of being a black box (the algorithms underlying the service are not available). On the other hand, an advantage is that the system is always maintained and updated by on-site experts, and improvements are always implemented in the applications.

To implement the decision support module, we used the IBM Watson Natural Language Classifier, a service that, with cognitive computing techniques, classifies short text phrases in predefined classes. Since this is a commercially-available service, its implementation algorithms are proprietary and likely based on DL techniques. It is however a supervised learning system, that was trained using annotated examples. To do so, we implemented 10 classes, one for each of the 10 most common TMDs with a specified validity of the clinical diagnostic criteria. We then defined a set of 500 sample sentences that were attributed to each class, extracting them either from the available literature or from the interviews with expert professionals. These samples were used as the training set for the service.

To implement the educational/informative module, we used IBM Watson Retrieve and Rank, a service that acts as an advanced search engine able to get answers to natural-language questions. Starting from the available literature, we constructed structured documents related to TMDs. To prepare the documents, the selected information sources were formatted in *answer units*, which are short paragraphs likely usable as answers. A set of 150 training questions each attached to an answer unit was then prepared and provided to the service and was used for training. Note that this service is now deprecated for the new Watson Discovery service. Therefore, after this prototype, the system should be revised and updated.

2.3 | System implementation

The application requirements were identified to overcome the barriers to the adoption of the system, as suggested by preliminary interviews with possible users. Identified requirements were:

- the system should only suggest possible answers with associated probabilities
- the system should not present a single answer
- the information sources relevant for each answer should be referenced to verify the suggestion

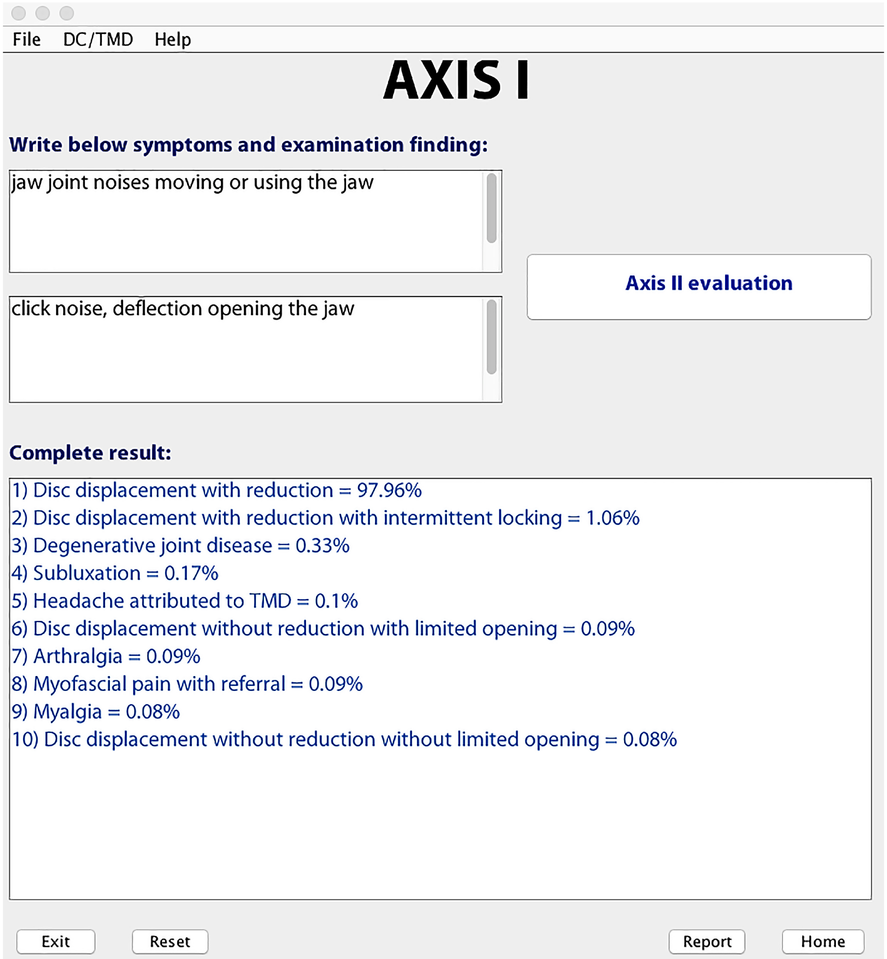

FIGURE 3 Natural Language Classifier user interface. DC/TMD, diagnostic criteria for TMD; TMD, temporomandibular disorder

Also, we identified relevant non-functional requirements: intuitive and usable interface, flexibility to updates, fast access to relevant information sources, cross-platform and privacy maintenance.

A graphic user interface and an operating system independent software were developed using Java with NetBeans 8.2 IDE. To allow integration in the application, IBM services were implemented using Node-RED, a flow-based programming tool shown in Figure 2.

2.4 | System proof-of-concept

The preliminary testing of the system included an evaluation of both performance and usability.

Regarding the decision support module, the performance evaluation was done retrospectively, using the decision support module to review available clinical cases, with a confirmed diagnosis. The evaluation included six cases. The cases used for the retrospective evaluation were those with an available complete electronic health record and for which we were able to reach patients and obtain additional consent to the secondary use of data. The system was queried using the symptoms reported by the patients, as indicated in the patient's medical record, and the list of possible diagnoses was reviewed against the final diagnosis. To account for the retrospective nature of the experiment, the test was repeated starting with the first three symptoms reported and continued by increasing the number of symptoms.

Regarding the educational/informative module, the preliminary testing was done by expert professionals who reviewed the answers provided by the system and qualitatively evaluated their accuracy. This was the only possible testing available since the correctness of the answer can be assessed only by experts and not automatically. This test was however aimed at improving the knowledge base of the system, and not at evaluating its performance. Two TMD experts were involved and worked together to reach a consensus on the relevance of the answers proposed by the system, and to suggest better-suited answers, also coming from new documents. In this way, we collected inputs for the prototype refinement.

Then, the full application was validated by two TMD experts. The application was provided to the experts for free use, and a series of questions was asked to understand (1) the time-saving introduced by the system; (2) the relevance of the system for an expert professional; (3) the relevance of the system for a non-expert professional; (4) the overall system evaluation. Each question was answered on a 10-point Likert scale.

3 | RESULTS

3.1 | Decision support module

Figure 3 shows the graphic user interface of the module. It was composed of two text boxes in which the clinician indicates the symptoms observed on or reported by the patient. In each text box, it is possible to insert more than one symptom. After clicking the button on the right, the text box at the bottom of the screen reports the results of the system. Each possible diagnosis is reported together with the associated probability and ranked starting from the most probable. The module also includes the possibility to view the complete diagnostic criteria for each of the TMDs, thus allowing the user to refine the diagnosis with additional tests if needed.

The testing was conducted on seven retrospective cases, as reported in Table 1. The table reports the symptoms set providing the best result achieved and the percentage reported by the IBM service.

As shown in Table 1, the system provides, in all cases with real TMD, the correct diagnosis among the most probable. In 4 out of 7 cases (57%), the first diagnosis corresponded to the correct diagnosis (full accuracy), and in 2 out of 7 cases (29%) the correct diagnosis was among the first three (partial accuracy), with a total of 86% correct answers. Only in one case (14%) the system was unable to provide an answer, and the classification failed. Note that the last two cases, 6 and 7, were used to test pathologies for which the system was not specifically trained, to account for misdiagnoses. The results were in both cases below the 10% threshold, which, in case 6 corresponded to a correct answer because it was a NoTMD case. In cases 4 and 5, however, where the system received generic symptoms, it provided several possibilities with similar ranking, thus being unable to identify the correct answer. This is however in line with the expected behaviour of the decision support, as it is intended to help non-expert dentists in deciding whether or not to refer the patient to a TMD specialist.

In addition to this retrospective assessment, the system was provided to two expert clinicians for usability testing. In a clinical environment, they queried the application respectively with symptoms and clinical findings and with questions about TMDs.

In general, they provided positive feedback (Table 2, lines 1–3). They observed that the decision support module could be very useful for non-expert clinicians, like general practitioners, physiotherapists and maxillofacial surgeons. This on-the-field test allowed clinicians who were not experts in TMDs to refine the decision support module user. One specific suggestion was to add a new section dedicated to the patient's evaluation using Axis II of the DC-TMD, thus allowing a psycho-social assessment of the patient. This section is represented in Figure 3 as the button on the right side of the screen, but it is not yet implemented.

TABLE 1 Clinician's diagnosis (Diagnosis) versus decision support system suggestions (System results) using the symptoms extracted by the NLC (Symptoms included).

Case, *n*	Diagnosis	Symptoms included	System result
1	Arthralgia	Pain in the TMJ, Pain in the jaw eating food, pain located in the articular area, pain is modified holding teeth together	Arthralgia (40%) Myalgia (30%) Myofascial pain with referral (30%)
2	Arthralgia	Confirmation of pain locations in the TMJ, pain in the jaw, pain speaking, pain in the jaw increases chewing	Arthralgia (60%) Myalgia (20%) Myofascial pain with referral (20%)
3	Myalgia	Difficulty eating hard food due to pain, pain in the jaw, difficulty speaking for a long time due to pain, pain laughing, pain speaking	Myalgia (30%) Myofascial pain with referral (30%) Arthralgia (30%) Headache (10%)
4	Myalgia	Facial muscles pain, pain in front of ear, difficulty eating hard food due to pain, pain is modified opening the mouth or moving jaw forward or to the side, pain is modified holding teeth together	Myalgia (30%) Myofascial pain with referral (30%) Arthralgia (30%)
5	Myalgia	Facial muscles pain, masticatory muscles pain, assisted opening movement of the jaw is elastic, pain speaking	Myalgia (80%) Myofascial pain with referral (20%)
6	No TMD	Pain when yawning, noise when yawning, no articular noises, no pain when opening mouth, no movement reduction when opening mouth	Disc displacement with reduction (<10%)
7	Arthrosis	Sand-like noise at the left TMJ, muffled hearing on the left side, pain at the preauricular area, good mouth opening, normal end-feel	Arthrosis (<10%)

Note: Case 6 and 7 are the negative test cases. If system results were below the 10% threshold, we reported only the first result.
Abbreviations: NLC, Natural Language Classifier; TMD, temporomandibular disorder; TMJ, temporomandibular joint.

TABLE 2 Usability questionnaire results

Questions	Responses	
	Evaluator 1	Evaluator 2
How do you rank the time-saving introduced by the system?	3	3
Do you believe that the system is useful for a TMD expert?	3	3
Do you believe that the system is useful for non-expert clinicians?	9	9
Do you believe that the educational/informative module is useful?	9	9

Note: The scale used is a linear 1–10 score system, in which 10 is the highest score ("yes, definitely") and 1 is the minimum score ("no, absolutely not").

Abbreviation: TMD, temporomandibular disorder.

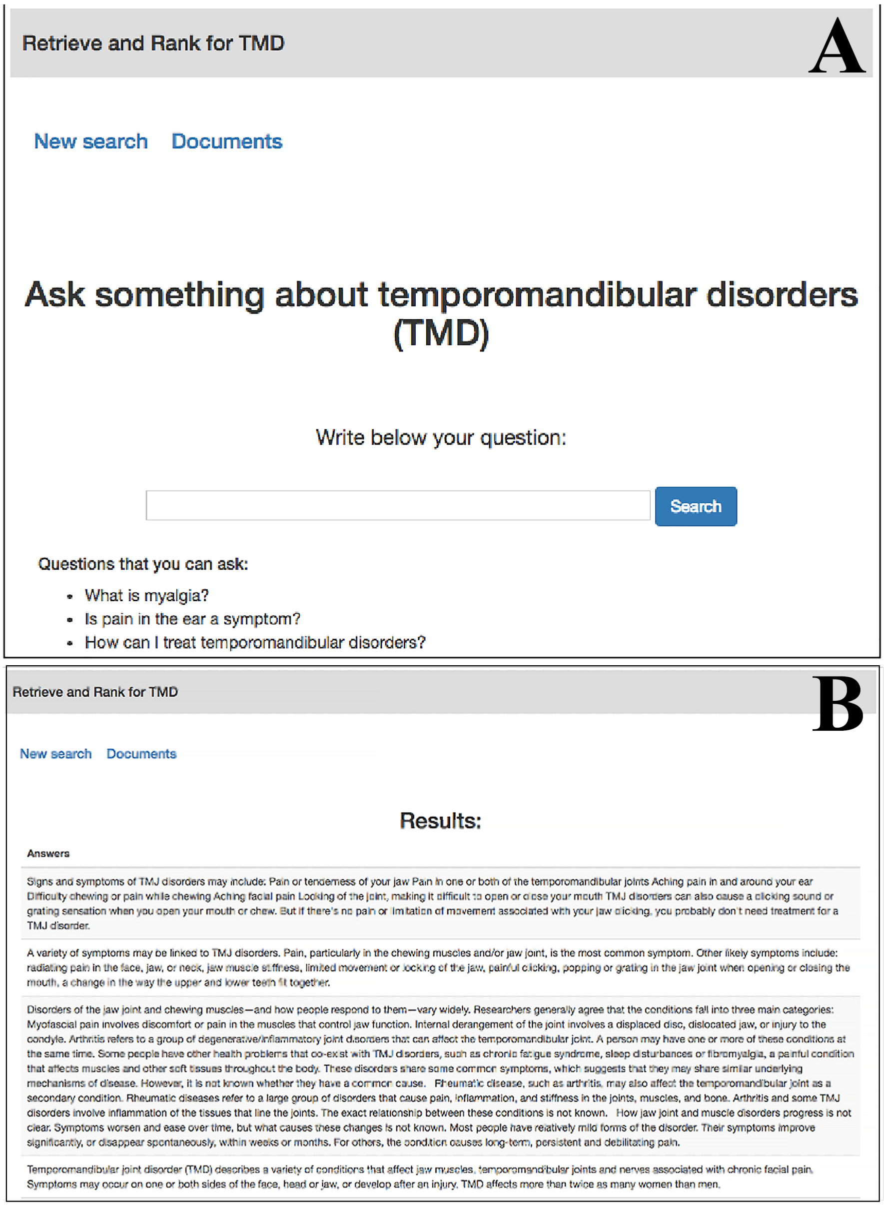

FIGURE 4 Application screenshots. (A) Informative/educational module home page. (B) ranking for keywords in the response.

3.2 | Informative/Educational module

Figure 4A shows the home page of the *Informative/educational module*, accessible by a common web browser. The user can write a question about TMD in natural language in the text box, and the service searches for the most appropriate answer in the documents available. A representative answer is shown in Figure 4B. The accuracy of the response was qualitatively evaluated by the two TMD experts involved. The system provided answers, in general, correct. However, according to the qualitative consensus evaluation of the two experts, better segmentation of the text would increase the answer's precision. As shown in Table 2, the usability questionnaire in *the educational/informative* module could be useful for TMD experts to quickly and easily upgrade their knowledge with the last research and discoveries in their field.

4 | DISCUSSION

In this work, we designed and implemented a proof-of-concept of a dual-module system, based on cognitive computing, aimed to provide support to untrained dentists dealing with TMDs. The system is grounded on the diagnostic criteria for TMD (DC-TMD) as basic knowledge for the decision support module. It analyses a textual input indicating the observed symptoms and shows a possible range of pathologies, with associated ranking. The other module is a question & answer system in which the user inputs questions that are answered through segments of the literature used for training.

The results were generally satisfactory. Both modules showed their ability to understand sentences not syntactically completed as well as synonyms of terms used in the training phase. This aspect, combined with the facilitated interaction based on the use of a natural language, was recognised as a promising feature by the dental professionals involved in the testing phase.

Our proposed prototype starts answering the unmet problem of challenging TMD diagnosis. Most of the previous experiences in AI-supported TMD diagnosis were based on imaging data that allow large training datasets. All studies showed encouraging results, even superior to those achieved here.[9] However, the decision to use an imaging technique for the diagnosis might be useful in specific and less frequent disorders, especially as it is usually taken when the patient is referred to a TMD specialist. Despite its limitations, our preliminary prototype is positioned in an earlier stage, when the patient is followed by generic dentists and refers to possible TMD-related symptoms. In fact, knowledge about TMD among the population is low and patients with TMD may seek treatment from different specialists, but dentists remain the main reference.[19] In addition, the chronic pathophysiological mechanism of TMDs (3 months after the onset of symptoms) leads to a worse prognosis. This suggests the importance of an earlier recognition and assessment of the above-mentioned disorders.

Our prototype is therefore not intended to substitute the expert in the diagnostic process, but it was conceived to help bridge the knowledge gap between "estimated treatment need and actual treatment carried out" in TMD patients. In fact, since TMD diagnosis is a long process based mainly on medical history, examination and imaging, there is evidence suggesting that these disorders are largely undetected.[5] The lack of appropriate training in undergraduate students may be a factor involved in such a gap, as suggested by Reissmann and colleagues, who showed that younger dentists with few years since graduation tended to underestimate the frequency of TMD treatment need.[7] To reduce this knowledge, gap some authors proposed the introduction of validated 3-screening questions (3Q/TMD) to be used in the general adult population to identify patients in need of further TMD examination.[5,20] Similarly, our system was proposed to create more awareness and try to facilitate the primary diagnoses of a TMD, even by a non-expert (dentists with fewer years since graduation), thus possibly improving the underestimation of TMD impact.

In the literature, there are only a few examples of ML-AI systems working on symptoms and natural language to support TMD diagnosis,[17,18] and they are mainly focused on differential diagnosis. Interestingly, Nam and colleagues[17] used text mining to extract the words used for symptom description by patients and found that by combing the most used words with clinical features (such as mouth opening size), the system had a predictive performance of 97%. Their approach is similar to ours in the use of natural language as system input, but then they used word frequency and clinical symptoms in a more classical statistical framework (multivariate logistic regression), instead of using a trained AI system. Also, we defined as a requirement the fact that the system should not suggest a single diagnosis as a response, but a set of possible diagnoses with an associated probability. This increases the transparency of the decision support, and allows the clinician, if needed, to prosecute the diagnostic pathway with specific tests to confirm the most probable diagnosis. The other work[18] applied a neural-network approach to classifying the type of TMD using clinical symptoms as input. They obtained different performances for different diagnoses, and, similarly to our results, the detection of disc displacements without clear characteristic symptoms was more difficult (around 40% sensitivity).

However, our prototype has limitations and requires further developments to achieve a fully functional system. The main limitation of the decision support module is the inability to differentiate between general and specific classes when few symptoms are given and all of them are in common between classes (e.g. Myofascial pain from myalgia). This could be overcome, however, by developing a hybrid application consisting of a cognitive system, which collects the symptoms in natural language, and a deterministic part in which specific questions are raised to the final user to correctly identify the disease. Preliminary development of this second aspect is presently ongoing. Second, in its present development, the classifier is not trained to recognise inputs not related to TMDs or, in general, to medicine. This has to be fixed in a future implementation of the NLC, adding examples of another class "unrelated to TMDs."

Another limitation regards the educational/informative module that requires a highly time-consuming training phase. At least 150 questions and a domain expert to detect the appropriate questions and properly assess the accuracy of given answers are needed to achieve minimally satisfactory results.

Finally, IBM Watson may not be the ideal technology to support a fully functioning system. While in these preliminary phases the use of a commercial solution allows the achievement of reliable solutions in less development time, in the long-period view, open-source solutions would allow the implementation of more inclusive services that can be provided to the scientific and research community without restrictions. Also, the low number of cases used for retrospective evaluation limits the possibility to draw final conclusions, and larger testing will be needed to test the new versions of the prototype.

In conclusion, despite these limitations, we provided a preliminary proof of concept of the feasibility to implement an AI-based system aimed to support non-specialists in the early identification of TMDs, possibly allowing a faster referral to second-level medical centres. This tool is useful to encourage general dentists in a primary diagnosis of a TMD and avoid suboptimal recognition and management in interdisciplinary treatment.

AUTHOR CONTRIBUTIONS

BR collected the data, conceived and designed the system testing, drafted the manuscript; LC system testing, manuscript critical review and check; MP performed the analysis and drafted the paper; EG system implementation; GD data analysis and collection, manuscript revision; SR conceived and designed the system, designed testing, drafted and reviewed the manuscript.

CONFLICT OF INTEREST

All authors declare that they have no competing interest.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/joor.13383.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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