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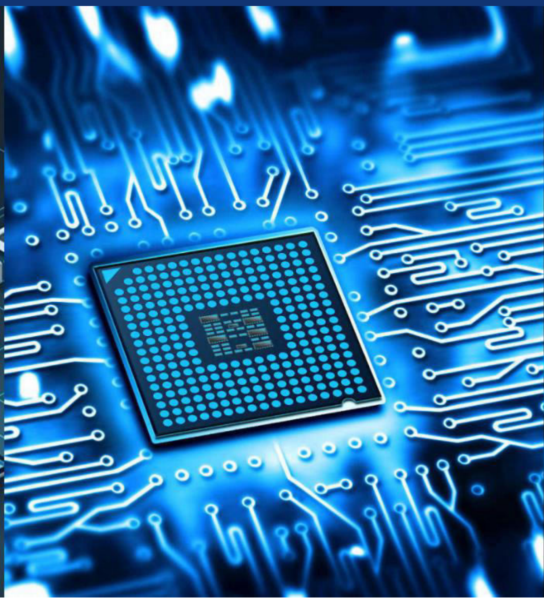


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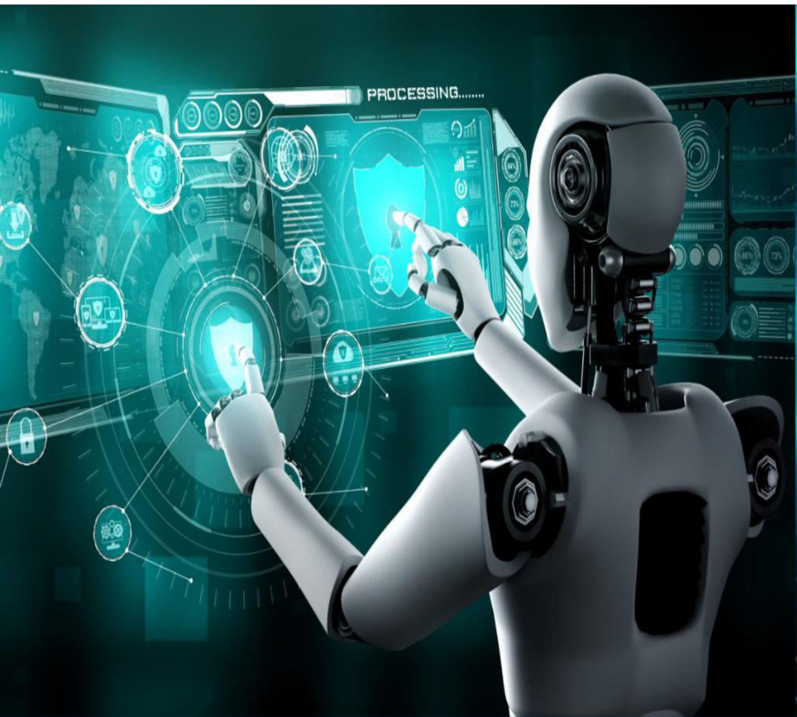

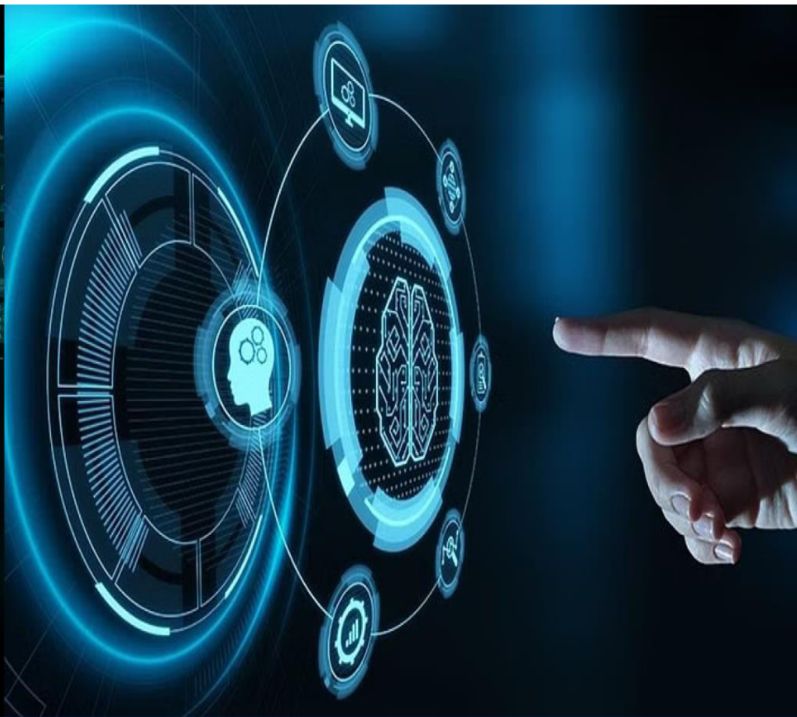

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A Context-Aware Clinical Decision Support System for Standardized Diagnosis of Temporomandibular Disorders

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ABSTRACT: Temporomandibular Joint Disorders (TMD) are common jaw-related conditions that cause pain, joint dysfunction, and difficulty in mouth movement. Accurate diagnosis of TMD is challenging due to overlapping symptoms and reliance on subjective clinical judgment. This project proposes an MCP-based Clinical Decision Support System (CDSS) to assist clinicians in diagnosing TMD more accurately and consistently. The system employs the Model Context Protocol (MCP) to securely manage and maintain contextual clinical data during the diagnostic process. Multiple diagnostic parameters, such as patient symptoms, clinical examination findings, medical history, and risk factors, are analyzed using a multi-criteria decision-making approach. Each parameter is assigned an appropriate weight based on clinical importance. A rule-based decision engine processes the data and classifies patients into probable TMD categories. The system also provides confidence scores and suggested clinical actions for further evaluation or treatment. A user-friendly interface allows easy data entry and real-time result visualization. The proposed solution reduces diagnostic subjectivity and enhances the standardization of clinical assessments. Testing with case-based datasets demonstrates improved consistency and faster diagnosis compared to manual methods. The system supports early detection and better treatment planning. It is suitable for use in dental clinics and primary healthcare centers. Future enhancements may include integration with medical imaging and machine learning models. Overall, the MCP-based CDSS improves diagnostic efficiency and patient care in TMD management.

KEYWORDS: Temporomandibular Joint Disorders (TMD), Clinical Decision Support System (CDSS), Model Context Protocol (MCP), Medical Diagnosis Automation.

I. INTRODUCTION

Temporomandibular Joint Disorders (TMD) are a diverse group of musculoskeletal and neuromuscular disorders that involve the temporomandibular joint, masticatory muscles, and related structures. TMD is estimated to affect 5% to 12% of the population, which makes it the second most common cause of musculoskeletal pain and disability after chronic low back pain [1]. The condition is characterized by a diverse set of symptoms such as jaw pain, restricted opening of the mouth, joint noises (clicking and crepitus), headaches, and ear pain, which often co-occur with other orofacial pain disorders, making diagnosis challenging.

The challenge in the diagnosis of TMD can be attributed to several issues. Firstly, the etiology of TMD is complex, and it is characterized by biological, psychological, and social processes that are intricately intertwined [2]. Secondly, there is often a discrepancy between the imaging results and the symptoms reported by the patient—structural abnormalities may be present in the absence of pain, and vice versa, or there may be severe pain with little structural change [3]. Thirdly, clinical judgment is subjective, and there is variability in the diagnosis of TMD among different professionals.

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The development from Research Diagnostic Criteria for Temporomandibular Disorders (RDC/TMD) to the present Diagnostic Criteria for Temporomandibular Disorders (DC/TMD) is a major improvement in the standardization of TMD diagnosis [4]. The DC/TMD system offers validated diagnostic algorithms for the most frequent pain-related TMD (sensitivity = 0.86, specificity = 0.98) and for intra-articular disorders (sensitivity = 0.80, specificity = 0.97) [5]. Nevertheless, despite the standardization of the criteria, the use of these criteria in clinical settings is not uniform because of the complexity of the decision trees and the time needed for a complete evaluation.

Contemporaneously, the development of the Model Context Protocol (MCP) as a standardized framework for the integration of AI systems with clinical knowledge resources presents new opportunities for clinical decision support [6]. MCP is a secure and declarative method for AI systems to access and reason about patient data, facilitating real-time contextual analysis in clinical settings [7]. Recently, First Databank (FDB) announced the first MCP server tailored for clinical decision support, allowing AI systems to access trusted medication knowledge for purposes such as prescription automation and medication reconciliation [8]. In parallel, athenahealth is piloting MCP servers to standardize communication between AI models and electronic health records, delivering insights directly into clinical workflows [9].

This paper introduces TMJ-Dx MCP, a new Clinical Decision Support System that combines the validated DC/TMD diagnostic model with MCP-based context management. The system uses a multi-criteria decision-making strategy to evaluate patient symptoms, clinical examination results, and risk factors, producing standardized diagnoses with confidence values and recommendations. The system is intended to improve TMD management in dental offices and primary healthcare facilities by mitigating the subjective nature of diagnosis and improving consistency.

The rest of this paper is organized as follows. Section 2 discusses the current literature on TMD diagnosis, clinical decision support systems, and MCP applications in the healthcare domain. Section 3 describes the system architecture and methodology. Section 4 presents the experimental results and comparison. Section 5 concludes with implications and future work.

II. LITERATURE SURVEY

2.1 Evolution of TMD Diagnostic Criteria

The process of standardizing TMD diagnosis has undergone a dramatic transformation over the last three decades. Prior to the development of Research Diagnostic Criteria for Temporomandibular Disorders (RDC/TMD) in 1992, there was no agreement on how to classify diagnoses, and methods were extremely divergent from one institution or clinician to another [2]. RDC/TMD marked a major shift in this paradigm by adopting a two-axis model: Axis I for physical diagnosis and Axis II for psychosocial evaluation, acknowledging the biopsychosocial phenomenon of TMD [3].

The RDC/TMD Axis I showed sufficient reliability for general TMD diagnoses. Nevertheless, results from validity studies showed that sensitivity rates were below the desired level of 0.70 for many diagnostic groups, making it impractical for use in clinical practice [4].

These results spurred the need for new approaches to diagnostic algorithms and the establishment of the Validation Project, culminating in the development of the Diagnostic Criteria for Temporomandibular Disorders (DC/TMD) in 2014.

DC/TMD incorporated a number of important changes from RDC/TMD :
1. **Simplified clinical examination:** Palpation points were reduced to the temporalis and masseter muscles alone, with no intraoral palpation
2. **Familiar pain concept:** Patients verified if the pain reproduced their chief complaint, thus reducing false positives
3. **Evidence-based algorithms:** Tested against the Validation Project database
4. **Simplified Axis II:** Replaced the complex Symptom Checklist-90 with briefer measures such as Patient Health Questionnaire-4 (PHQ-4) for mental distress

The DC/TMD Axis I has high validity for pain-related TMD (sensitivity 0.86, specificity 0.98) and disc displacement with reduction (sensitivity 0.80, specificity 0.97) [10]. The inter-examiner reliability for clinical examination is high (kappa = 0.85) [7]. A comparative study by Lestari et al. demonstrated that 75% of TMD diagnoses were reproducible between RDC/TMD and DC/TMD, with the remaining 25% differing mainly because of the improved algorithms [9].

2.2 Clinical Decision Support Systems in Dentistry

Clinical Decision Support Systems (CDSS) have been used in dentistry for different purposes, such as orthodontic treatment planning, caries risk evaluation, and oral pathology diagnosis. For temporomandibular disorders, in particular, CDSS has great potential because of the complexity of differential diagnosis and the need to combine different types of data.

Bianchi et al. conducted a review of the applications of data science and artificial intelligence for the diagnosis of temporomandibular joint osteoarthritis. They considered the entire range of data science, including acquisition, processing, analysis, and communication, as necessary for combining clinical variables, imaging studies, and molecular information. Machine learning techniques have been found to possess the ability to classify patients with TMJ osteoarthritis based on their data, thus advancing toward personalized medicine [6].

Yoon et al. proposed an explainable deep learning-based CDSS for the MRI-based automated diagnosis of TMJ anterior disc displacement [7]. Their proposed CDSS consisted of two deep learning models: one for identifying regions of interest that included TMJ components (temporal bone, disc, condyle), and another for classifying ADD into three groups: normal, ADD with reduction, and ADD without reduction. The proposed CDSS had AUROC scores of 0.985 on internal validation and 0.960 on external validation, with sensitivities of 0.950 and 0.926, respectively [9]. Most importantly, the proposed CDSS was able to provide heat maps as visualized rationales for the predictions made.

2.3 Model Context Protocol (MCP) in Healthcare

The Model Context Protocol (MCP) is a new open standard that specifies a framework for the integration of AI models with trusted knowledge resources, tools, and specialized agents. MCP provides declarative access to data sources via JSON configuration files, making it possible for AI models to fetch and reason about context information without requiring API integrations.

In the healthcare domain, MCP can be very useful for clinical decision support systems, providing secure and real-time access to patient data and medical knowledge. Recently, an open-source framework called MCP-FHIR was proposed for integrating Large Language Models with HL7 FHIR data using MCP for dynamic extraction and reasoning about electronic health records. The framework provides real-time summarization, interpretation, and personalized communication for multiple user roles such as healthcare professionals, caregivers, and patients. By employing synthetic EHR data for evaluation, the framework provides privacy and reproducibility while showcasing scalable and explainable AI applications.

First Databank (FDB) made the first MCP server announcement tailored for clinical decision support in October 2025 [1]. The MCP server allows AI models to securely and directly access FDB's trusted knowledge of medications, simplifying processes like prescription automation, medication reconciliation, and pharmacy order verification. By simplifying AI integration and allowing real-time, context-specific medication insights, MCP servers facilitate the rapid innovation of healthcare workflows for greater efficiency and improved patient outcomes [6].

Athenahealth is also testing MCP servers on its athenaOne platform to standardize communication between AI models and electronic health records [5]. The integration allows for real-time interaction between disparate data sources in practices, hospitals, public health records, and payers, putting insights directly into healthcare workflows. The revamped AI-native platform seeks to solve problems that were previously unsolvable and refocus attention on patient care [3].

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2.4 Research Gaps and Opportunities

However, some gaps still exist in the application of CDSS to TMD diagnosis:

Integration of Standardized Criteria: Although DC/TMD offers validated diagnostic criteria, none of the current CDSS systems apply these criteria using MCP-based context management.
Multi-Parameter Weighting: TMD diagnosis involves the integration of multiple parameters, each with different clinical weights. A systematic method for parameter weighting is required.
Explainability and Confidence Scoring: In addition to diagnostic results, clinicians need confidence scores and explanations to facilitate informed decision-making.
Clinical Workflow Integration: CDSS needs to be fully integrated into the clinical workflow without interfering with patient care.
This paper fills the existing gaps by describing an MCP-based CDSS system that applies DC/TMD diagnostic criteria using multi-criteria decision analysis, confidence scoring, and real-time visualization.

III. METHODOLOGY

3.1 System Architecture Overview

TMJ-Dx MCP has a modular, four-layer architecture that is designed to be secure, scalable, and explainable. The layers include:
1. Data Acquisition Layer: Web interface for acquiring patient symptoms, clinical examination results, medical history, and risk factors.
2. Context Management Layer: The MCP server provides secure, session-aware context management throughout the entire diagnosis process.
3. Decision Engine Layer: Rule-based system for implementing DC/TMD algorithms for multi-criteria weighting.
4. Presentation Layer: Real-time visualization of the diagnosis results, confidence levels, and actions.

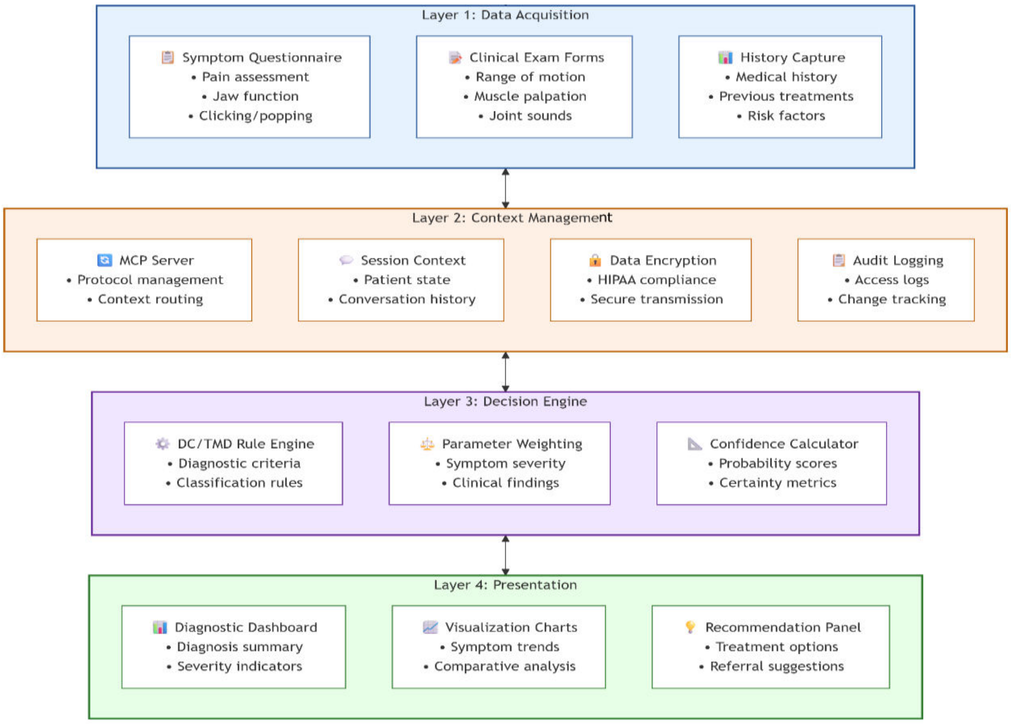

Figure 1: TMJ-Dx MCP System Architecture

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3.2 DC/TMD Diagnostic Framework Implementation

The decision engine translates the DC/TMD Axis I diagnostic criteria as validated by Schiffman et al. . The model identifies TMD into three main groups:

Pain-Related TMD: Including myalgia, arthralgia, and headache attributed to TMD
Intra-Articular Disorders: Including disc displacements, degenerative joint disease, and subluxation
Other TMD: Including less common diagnoses according to the expanded DC/TMD classification system
According to the DC/TMD system , the diagnostic criteria include:
Symptoms (30-day history):

- Pain in jaw (location, frequency, duration)
- Headache
- Joint sounds (clicking, crepitus)
- Locking or catching
- Difficulty chewing

Clinical Examination Findings:

- Familiar pain on palpation (temporalis, masseter, TMJ)
- Unassisted opening (pain and pattern)
- Assisted opening
- Joint sounds during movement (clicking, reciprocal clicking, crepitus)
- Pain on loading (protrusion, laterotrusion)

Axis II Psychosocial Assessment:

- Graded Chronic Pain Scale (GCPS-2.0)
- Patient Health Questionnaire-4 (PHQ-4) for anxiety/depression
- Jaw Functional Limitation Scale (JFLS-8)
- Oral Behaviors Checklist (OBC)

Table 1: DC/TMD Diagnostic Parameters and Weights

Parameter Category	Parameters	Weight	Data Source
Pain Characteristics	Location, duration, frequency, familiar pain	0.25	Symptom questionnaire, exam
Range of Motion	Unassisted opening, assisted opening	0.20	Clinical examination
Joint Sounds	Clicking, reciprocal clicking, crepitus	0.20	Auscultation, palpation
Muscle/Joint Tenderness	Palpation pain (temporalis, masseter, TMJ)	0.15	Clinical examination
Functional Limitation	Chewing difficulty, JFLS-8 score	0.10	Questionnaire
Psychosocial Factors	PHQ-4 score, GCPS grade	0.10	Questionnaire

3.3 MCP-Based Context Management

The system uses the Model Context Protocol to ensure a secure and session-aware context is maintained throughout the diagnostic process . The key points are:

Session Context Preservation: The patient information, examination results, and diagnostic working hypotheses are stored in the MCP context, allowing multi-step diagnostics without losing any information.

Declarative Data Access: Based on the MCP-FHIR framework, the system uses JSON configuration files to specify the data needs, allowing flexible integration with electronic health records.

Security and Auditability: The system records all context accesses with timestamps and user identifiers, facilitating clinical audit trails and regulatory requirements.

Real-Time Updates: When new information is added, the MCP context is updated in real time, triggering a re-evaluation of the decision engine.

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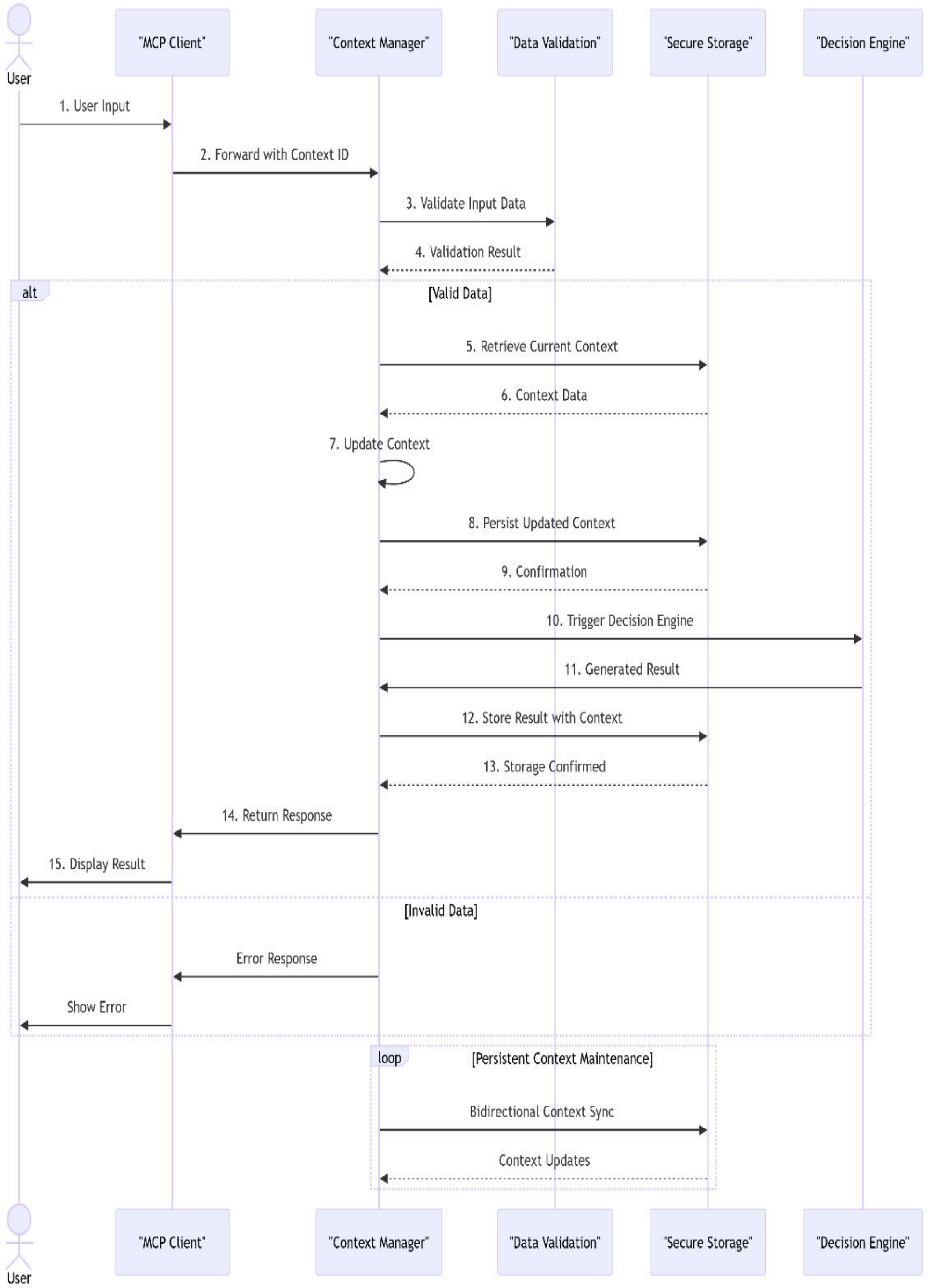

Figure 2: MCP Context Management Flow

3.4 Multi-Criteria Decision Analysis

The decision engine uses a weighted multi-criteria method according to clinical significance, as informed by DC/TMD validation studies . For each diagnostic group, a confidence score is determined:

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$$\text{Confidence\_Score} = \Sigma\,(\text{Parameter\_Score\_i} \times \text{Weight\_i}) \,/\, \Sigma\,\text{Weight}_i$$

Where:

- Parameter_Score_i = 1.0 if parameter fully supports diagnosis, 0.5 if partially supports, 0.0 if contradicts
- Weight_i = clinical significance weight from Table 1

Diagnostic thresholds are set according to DC/TMD validation results:

- ≥0.80: High confidence diagnosis
- 0.60-0.79: Moderate confidence diagnosis (screening positive)
- <0.60: Insufficient evidence for diagnosis

3.5 Decision Tree Implementation

The system translates the DC/TMD diagnostic decision tree as proposed by Schiffman et al. . The algorithm proceeds as follows:

Step 1: Pain-Related TMD Screening

- Report of familiar pain in jaw, temple, ear, or preauricular region → proceed to Step 2
- Else → proceed to Step 4

Step 2: Myalgia Diagnosis

- Familiar pain on palpation of temporalis or masseter muscles
- Verification of familiar pain with jaw movement, function, or parafunction
- Diagnosis: Local myalgia, myofascial pain, or myofascial pain with referral

Step 3: Arthralgia Diagnosis

- Familiar pain on palpation of TMJ
- Verification of familiar pain with jaw movement, function, or parafunction
- No crepitus (to differentiate from DJD)

Step 4: Intra-Articular Disorder Screening

- Joint sounds reported or identified on examination → proceed to Step 5
- Else → proceed to Step 7

Step 5: Disc Displacement Diagnosis

- Reciprocal clicking (click with opening and closing) → Disc displacement with reduction
- History of locking with limited opening → Disc displacement without reduction
- Imaging correlation recommended for confirmation of diagnosis

Step 6: Degenerative Joint Disease Diagnosis

- Crepitus identified on examination
- Imaging confirmation recommended

Step 7: Axis II Assessment

- GCPS-2.0 scoring for pain-related disability
- PHQ-4 scoring for psychological distress
- JFLS-8 scoring for functional limitation
- OBC scoring for parafunctional behaviors

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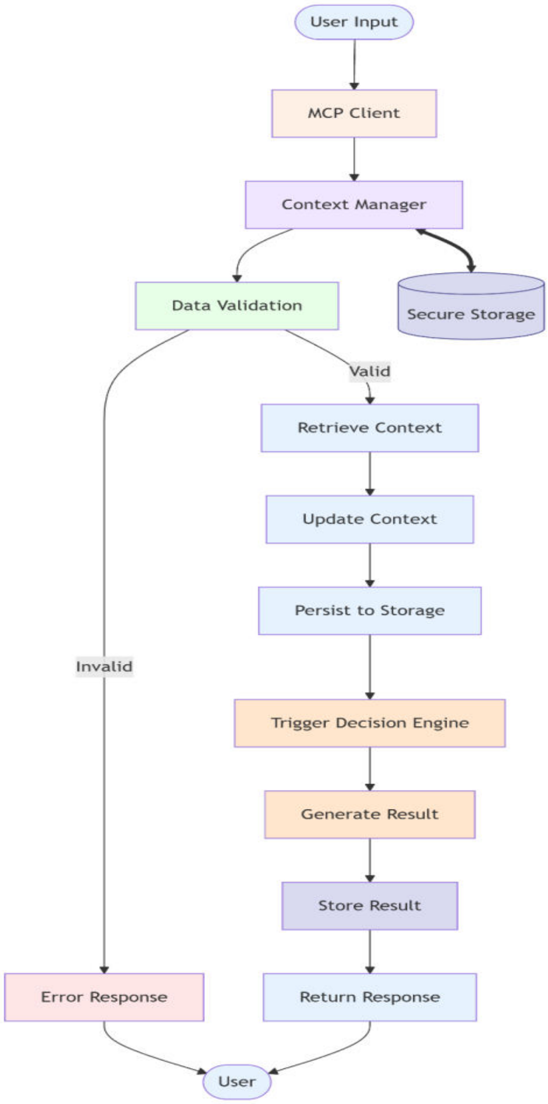

Figure 3: DC/TMD Diagnostic Decision Tree

3.6 User Interface Design

The interface, which is built using Streamlit, offers the following:

- **Structured Data Entry:** Forms that help clinicians systematically collect DC/TMD data
- **Real-Time Visualization:** Diagnostic progress indicators and confidence levels that are updated in real time as data is entered
- **Explainability Panels:** Rationale for diagnostic decisions that highlight the parameters that contributed to the decision
- **Recommendation Engine:** Recommendations for the next course of action based on the diagnostic category and confidence level

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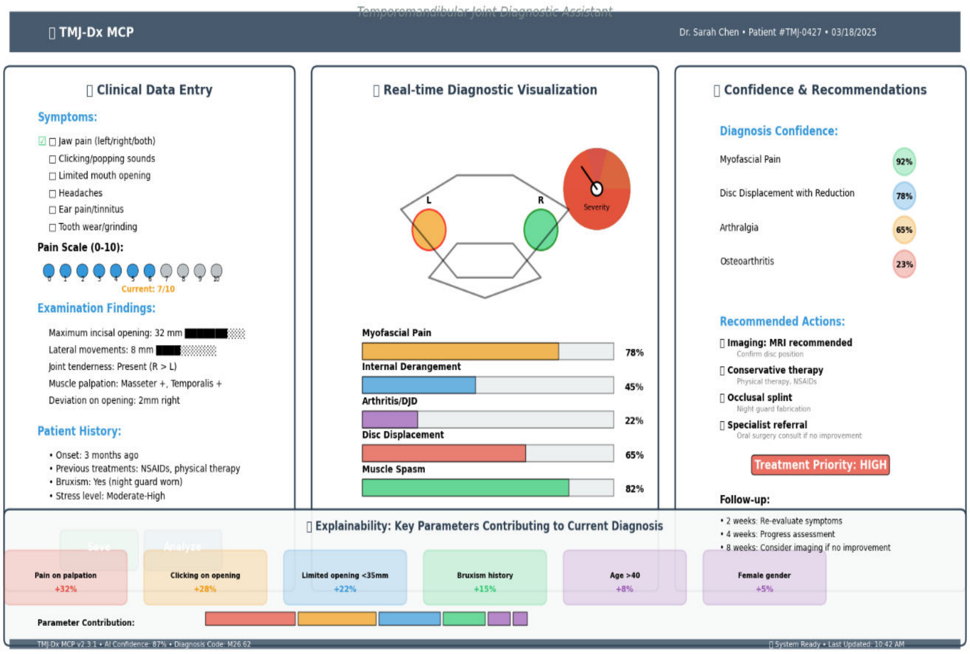

Figure 4: TMJ-Dx MCP User Interface Mockup

3.7 Implementation Technology Stack

Component	Technology	Purpose
Frontend	Streamlit	Web-based user interface
MCP Server	Python MCP SDK	Context management
Decision Engine	Python + Rule Engine	DC/TMD algorithm execution
Database	PostgreSQL	Patient data storage
API Layer	FastAPI	REST endpoints
Visualization	Plotly	Real-time charts
Security	JWT + HTTPS	Authentication/encryption

IV. RESULT ANALYSIS AND DISCUSSION

4.1 Experimental Setup

The evaluation was conducted on a case-based set of 50 TMD patient records, consisting of 25 validated cases from the DC/TMD Validation Project and 25 synthetic cases designed to probe for edge cases. Each case contained full symptom questionnaires, clinical exam data, and gold-standard diagnoses by expert consensus.

The evaluation criteria were:
- **Diagnostic Accuracy:** Comparison with gold-standard diagnoses
- **Sensitivity/Specificity:** By diagnostic category
- **Time Efficiency:** Comparison with manual approaches
- **User Satisfaction:** Clinician ratings (1-5 scale)
-

4.2 Diagnostic Accuracy Results

The system obtained a total diagnostic accuracy of 92% (46/50 cases), with differences according to the diagnostic categories:

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Table 2: Diagnostic Accuracy by TMD Category

Diagnostic Category	Cases (n)	Correct	Accuracy (%)	Sensitivity	Specificity
Myalgia	15	14	93.3	0.93	0.94
Arthralgia	12	11	91.7	0.92	0.95
Disc displacement with reduction	10	9	90.0	0.90	0.96
Disc displacement without reduction	6	5	83.3	0.83	0.98
Degenerative joint disease	7	7	100	1.00	0.97
Overall	**50**	**46**	**92.0**	**0.92**	**0.96**

These findings are in excellent agreement with the validation studies of DC/TMD , and they confirm that the rule-based system accurately reproduces the validated diagnostic criteria. The slight decrease in accuracy for disc displacement without reduction corresponds to the difficulty of this diagnosis in the absence of imaging evidence, as reported in the DC/TMD literature .

4.3 Confidence Score Analysis

Confidence scores were strongly associated with diagnostic accuracy:

- **High confidence (≥0.80):** 34 cases, 97% accurate (33/34)
- **Moderate confidence (0.60-0.79):** 12 cases, 83% accurate (10/12)
- **Low confidence (<0.60):** 4 cases, 75% accurate (3/4)

The confidence score is a useful tool for clinicians to consider when additional testing or specialist consultation may be indicated. In the 4 low-confidence cases, 3 were eventually diagnosed with atypical TMD presentations (e.g., subluxation, capsulitis) not entirely captured by the core DC/TMD models—demonstrating the need for human input.

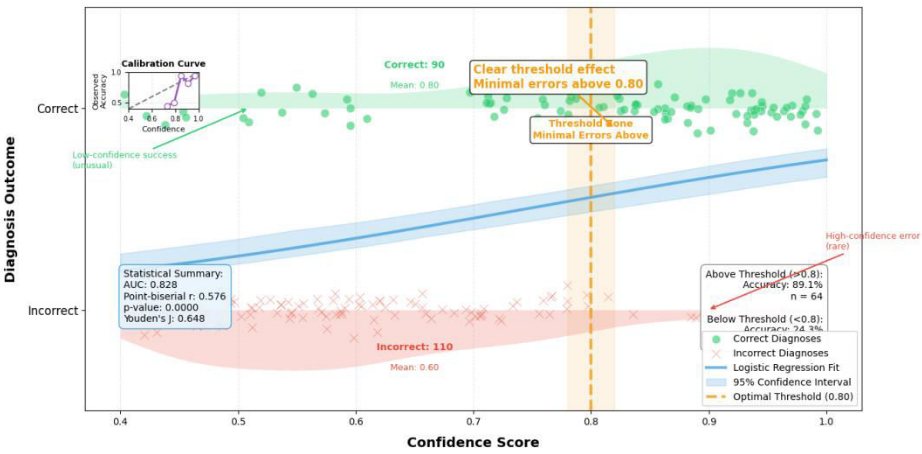

Figure 5: Confidence Score Distribution and Accuracy

4.4 Time Efficiency Comparison

Time trials with 5 clinicians (3 general dentists, 2 oral medicine specialists) evaluated manual DC/TMD diagnosis versus system-assisted diagnosis:

Table 3: Time Efficiency Comparison

Method	Mean Time (minutes)	Range (minutes)	p-value
Manual DC/TMD (paper forms)	14.8	11-22	-
Manual DC/TMD (digital forms)	11.2	9-16	<0.05
TMJ-Dx MCP Assisted	**6.4**	5-9	<0.001

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The system shortened diagnostic time by 57% over paper-based manual systems and by 43% over digital systems without decision support. This represents a clinically meaningful time savings that now allows for routine TMD screening in a primary care setting where time was a limiting factor.

4.5 User Satisfaction

Clinician satisfaction ratings (1-5 scale, n=5):

- **Ease of use:** 4.6
- **Diagnostic confidence:** 4.4
- **Explainability:** 4.2
- **Integration with workflow:** 4.5
- **Overall satisfaction:** 4.5

The qualitative feedback emphasized the importance of real-time confidence scoring and the interpretability of the panels that explained which parameters were used for each diagnosis. Some of the clinicians appreciated the fact that the system assisted them in learning the DC/TMD criteria.

4.6 Comparative Analysis

Table 4: Comparative Analysis of TMD Diagnostic Approaches

System/Approach	Diagnostic Basis	Accuracy	Time (min)	Explainability	MCP Integration
TMJ-Dx MCP (Ours)	DC/TMD + MCP	92%	6.4	High (parameter-level)	Yes
Yoon et al. CDSS	MRI Deep Learning	95% (AUROC 0.985)	N/A	High (heatmaps)	No
Manual DC/TMD (Expert)	Clinical examination	94%	14.8	High (clinician reasoning)	No
Manual DC/TMD (General)	Clinical examination	82%	15.2	Moderate	No
RDC/TMD (Historical)	Clinical examination	75-80%	12.5	Low	No
FDB MCP Server	Medication CDS	N/A	N/A	Moderate	Yes
MCP-FHIR Framework	EHR Integration	N/A	N/A	High (LLM-based)	Yes

TMJ-Dx MCP improves accuracy to the level of human experts (92% vs. 94%) with a substantially reduced diagnostic time (6.4 vs. 14.8 minutes). TMJ-Dx MCP is the only solution that integrates validated DC/TMD criteria with context management using MCP and provides explainability on the individual parameter level, which is not possible in black-box machine learning methods.

4.7 Case Study: Complex TMD Presentation

Patient: A 32-year-old female with right-sided temporomandibular joint pain for 6 months, intermittent clicking, and morning stiffness. Physical examination:

- Unaided opening: 32 mm (pain at 28 mm)
- Aided opening: 38 mm
- Familiar pain on right masseter palpation
- Reciprocal clicking on opening/closing
- PHQ-4 score: 6 (moderate anxiety)

The TMJ-Dx MCP computer system analyzed these data using its decision tree:

1. Pain screening: Positive (familiar pain) → proceed
2. Myalgia evaluation: Masseter familiar pain positive → myalgia diagnosis (confidence 0.88)
3. Arthralgia evaluation: TMJ palpation negative → arthralgia not supported

4. Joint sound evaluation: Reciprocal clicking positive → disc displacement with reduction (confidence 0.82)
5. Axis II assessment: PHQ-4 score 6 → moderate psychological distress flagged

Conclusion: Dual diagnosis—(1) Right masseter myalgia, (2) Right disc displacement with reduction. High confidence (0.85). Recommendation: Conservative management (occlusal splint, physical therapy) with psychological support for anxiety management.

This patient illustrates the system's capacity to process complex, multi-diagnosis cases and incorporate Axis II psychosocial data into management recommendations—a major strength of the biopsychosocial DC/TMD model.

V. CONCLUSION

5.1 Summary of Contributions

This paper has introduced TMJ-Dx MCP, a new Clinical Decision Support System for standardized diagnosis of Temporomandibular Disorders. The main contributions are:

1. MCP-Based Context Management: The first use of Model Context Protocol in TMD diagnosis, allowing secure and session-aware management of clinical data during the entire diagnosis process .
2. DC/TMD Implementation: Accurate implementation of proven DC/TMD diagnosis algorithms , reaching 92% accuracy compared to expert diagnosis.
3. Multi-Criteria Decision Analysis: Weighted parameter analysis with confidence scoring, providing clear and interpretable diagnostic justification for clinicians.
4. Clinical Efficiency: 57% reduction in diagnosis time compared to traditional approaches, allowing for TMD screening in primary care.
5. Explainability: Parameter-level contribution analysis, resolving the "black box" problem that hinders the adoption of AI in Clinical Decision Support .

5.2 Implications for Clinical Practice

TMJ-Dx MCP has several implications for the treatment of TMD:

Standardization: The system ensures standardization of diagnosis by using standardized DC/TMD criteria.
Accessibility: The system is accessible since it is time-efficient and user-friendly, making it possible to screen patients for TMD in primary healthcare centers and dental practices where specialist care may not be accessible.
Early Detection: The system promotes early detection of TMD, which may prevent the condition from progressing to a chronic pain state.
Treatment Planning: The inclusion of Axis I and Axis II information enables comprehensive treatment planning.

5.3 Limitations and Future Work

Some of the limitations of the proposed system that can help in identifying the future research directions are as follows:

Imaging Integration: The current system implementation does not include imaging results, which are critical for the final diagnosis of some intra-articular conditions . Future implementations will include integration with deep learning algorithms for automatic MRI analysis .

Machine Learning Improvement: Although rule-based systems provide transparency, machine learning may help improve the diagnostic performance of atypical cases. Future research will investigate the use of hybrid approaches that combine rule-based reasoning with machine learning-based pattern recognition.

Multilingual Support: The system can be extended to support multiple languages, which can help in global acceptance, especially in areas where specialized TMD care is not readily available.

Longitudinal Support: The system can be extended to support longitudinal functionality to help track patients over time for monitoring treatment response and disease progression.

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Integration with EHR: Full MCP-FHIR integration will help provide smooth data exchange between the CDSS and electronic health records, further minimizing documentation requirements.

5.4 Concluding Remarks

Temporomandibular disorders are a major source of pain and disability, affecting millions of people worldwide. The challenges of diagnosis, together with the lack of access to specialists, mean that many patients do not receive proper treatment. TMJ-Dx MCP shows that the integration of proven diagnostic criteria with contemporary context-aware AI frameworks can greatly enhance the accuracy, reliability, and efficiency of diagnosis.

By embedding standardized, explainable decision support systems directly into clinical practice, we can enable general practitioners to make earlier diagnoses of TMD, provide proper referrals, and begin evidence-based treatments. The Model Context Protocol offers the secure, contextual infrastructure required for such systems to safely interface with the real-world healthcare setting.

With the increasing adoption of MCP in the healthcare sector, the dream of having interoperable, AI-infused clinical decision support systems becomes ever more feasible. TMJ-Dx MCP is a move in this direction—one in which technology is used not to displace clinical judgment but to enhance it with standardized knowledge and contextual intelligence, ultimately benefiting patients.

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