Keywords
Generative Artificial Intelligence (GenAI), Clinical Decision Support System (CDSS), Prosthodontics, Personalized Treatment Planning, Large Language Models (LLMs)

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A GENERATIVE ARTIFICIAL INTELLIGENCE POWERED CLINICAL DECISION SUPPORT SYSTEM FOR PERSONALIZED TREATMENT PLANNING IN PROSTHODONTICS

Abstract
Generative Artificial Intelligence (GenAI) is revolutionizing the field of prosthodontics, where GenAI is used for providing intelligent decision support for treatment planning and prosthesis choice with respect to specific patients. In this retrospective multicenter validation study, the proposed Evidence grounded hybrid clinical reasoning framework (EHCRF) combines multimodal patient information, including demographics, medical history, intraoral examination, radiographs, occlusion, digital impressions, and preferences of clinicians in order to recommend personalized treatment plans. Specifically, in the proposed framework, a multimodal explainable AI system is developed, which leverages transformer-based large language models (LLMs), retrieval-augmented generation (RAG) based on semantic vectors, explainable artificial intelligence (XAI), multimodal data fusion, and prosthodontic evidence-based guidelines in order to provide transparent and context-sensitive decisions for clinical decision making. In terms of validation of the proposed framework, 1,248 cases were assessed in the validation set by 25 experienced prosthodontists compared to CAD/CAM-based treatment planning driven by experts. Consequently, the proposed approach resulted in 96.8% diagnostic accuracy (95% confidence interval [CI]: 95.7-97.9%), 95.9% treatment recommendation agreement, 2.3 seconds average response time, and 4.8/5 clinicians' satisfaction (5-point Likert scale). All the above results showed statistically significant performance gain ($p < 0.001$). The main contribution is the creation of the evidence-based hybrid model of clinical reasoning that combines multimodal patient data, augmented reasoning with retrieval methods, explainable AI, and large language models into one prosthodontic decision support system

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INTRODUCTION

The field of prosthodontics is currently experiencing an important digital revolution due to the introduction of innovations in areas such as artificial intelligence, computational simulation and smart clinical devices, which will provide improvements to diagnosis, treatment planning and prosthetic rehabilitation procedures [1]. The utilization of artificial intelligence in prosthodontics has evolved beyond image processing and designing of prosthesis to smart decision-making systems that can help in clinical decision making in complex situations [2]. Recently, the advent of Generative Artificial Intelligence (GenAI) is creating a new avenue for smart clinical decision making and personalized therapy and thus providing the foundation for future intelligent prosthodontic systems [3].

1.1Digital Transformation in Prosthodontics

The development of digital technology has completely transformed prosthodontics by replacing traditional analogue procedures with integrated digital workflows that facilitate better diagnostics, treatment prediction, and prostheses' fabrication [4]. Modern digital prosthodontics comprises intraoral scanning, CBCT, facial scanning, CAD/CAM, and 3D printing technologies that create an integral ecosystem for prosthodontic treatment, reducing the number of errors that occur during the process and increasing clinical reproducibility [5]. With the help of such technologies, it has been possible to create highly accurate virtual reconstructions of patients that allow for better visualization of anatomical structures, simulating restoration results and optimizing prosthesis design prior to actual clinical work [6]. However, even with such technological advancements, modern digital workflows still largely depend on the clinician's software proficiency and require a high level of professional experience in order to process and interpret heterogenic clinical data, assess different treatment options and balance biological, functional and aesthetic aspects of treatment planning [7]. As a result, treatment planning is greatly dependent on personal clinical experience and involves variability in treatment decisions, which limits the standardization of the workflow in complex prosthodontic cases [8]. Thus, as digital prosthodontics evolves from computer-aided manufacturing to clinical decision-making support, the implementation of artificial intelligence seems to be a natural step towards making evidence-based personalized therapeutic decisions in the future.

1.2 Clinical Challenges in Personalized Treatment Planning

Personalized treatment planning in prosthodontics is one of the most complex clinical decision-making processes since it involves the integration of numerous patient-specific factors that include anatomy, functionality, biology, aesthetics, and systemic features and often have conflicting therapeutic priorities [9]. Modern prosthodontic rehabilitation approaches are required to analyze intraoral information, radiographic images, occlusal relations, periodontal conditions, medical history, patient expectations, and prognosis and find out the best possible prosthetic therapy [10]. The abundance of available digital diagnostic data makes it possible to significantly increase the variety of clinical information. Still, the transformation of these heterogeneous datasets into therapeutic recommendations largely depends on clinician's skills and experience [11]. This leads to potential discrepancies between the treatment decisions of different prosthodontists based on identical clinical evidence [12]. The current digital treatment planning platforms primarily help visualize and design prostheses without the possibility of conducting evidence-based reasoning, personalized recommendation generation, or justification of therapeutic options [13]. Thus, during development of prosthodontic rehabilitation towards precision dentistry, there emerges the need for intelligent decision-support systems which would be able to integrate multiple patient data with validated clinical knowledge to guide clinicians in providing standardized, personalized, and evidence-based treatment plans.

1.3 Generative Artificial Intelligence and Clinical Decision Support Systems

Artificial intelligence technologies have been developing from traditional machine learning and deep learning approaches towards Generative Artificial Intelligence (GenAI), which makes it possible for intelligent systems to conduct context-aware reasoning, knowledge synthesis, and evidence-based clinical recommendation generation [14]. The progress in LLMs based on transformers has significantly increased the ability of intelligent systems to understand complex clinical narratives, integrate heterogeneous biomedical information, and generate clinically relevant responses using natural language reasoning [15]. Together with the use of Retrieval-Augmented Generation (RAG), these systems can dynamically find and use the evidence in validated knowledge bases thus reducing unsupported responses and increasing the quality and transparency of recommendations [16]. In addition, Explainable Artificial Intelligence (XAI) has become an essential element of healthcare decision support, making it possible for intelligent systems to provide the interpretable reasoning pathways that would help clinicians to comprehend, validate, and trust the AI-assisted recommendations [17]. In prosthodontics, artificial intelligence has demonstrated significant potential in terms of implant planning, prosthesis design, digital impression analysis, restoration prediction, and treatment outcome evaluation. However, most existing applications of AI technology are task-specific and represent isolated analytical tools rather than the holistic decision-support ecosystems [18]. Hence, the current AI systems are not integrated in the framework which would make it possible to combine multimodal data fusion, knowledge retrieval, transformer-based reasoning, explainable recommendations, and personalized treatment planning. These issues call for the creation of next-generation GenAI-based Clinical Decision Support Systems (CDSS).

1.4 Research Gap and Motivation

Although there have been great improvements in artificial intelligence, the current applications in prosthodontics are limited to isolated tasks in the clinic, including diagnosis, planning of implants, designing of prostheses, and interpreting images, which do not offer overall personalized decision-making support for the prosthodontic workflow [19]. The AI-enabled methods mainly serve the task-specific analysis and do not have the ability to integrate the heterogenous clinical information into one decision support system. In addition, the current methods usually do not involve multimodal patient data, evidence-based knowledge retrieval, transformer-based clinical reasoning, explainable artificial intelligence (XAI), and clinician-based decision support in one clinically interpretable system [20]. These factors limit the applicability of AI-enabled decision support in prosthodontics in terms of clinical transparency, evidence traceability, scalability, and practicality [21]. In order to overcome the methodological limitation, the current paper suggests the unified Generative Artificial Intelligence-powered Clinical Decision Support System (GAI-CDSS), which develops an evidence-based clinical reasoning model by incorporating multimodal patient information, RAG, transformer-based large language models, XAI, and evidence-based prosthodontic guidelines into the intelligent decision-support system. In contrast to the existing task-specific AI methods, the new methodological framework offers the transparent, personalized, and clinically interpretable treatment recommendations in the prosthodontic treatment-planning workflow.

1.5 Research Objectives

The main purpose of this research is the development and validation of the Generative Artificial Intelligence-based Clinical Decision Support System (Evidence grounded hybrid clinical reasoning framework (EHCRF)) that would be able to support personalized prosthodontics treatment planning by using the integration of multimodal clinical information and evidence-based reasoning [22]. The goal of the proposed solution is to implement the combination of transformer Large Language Models, Retrieval-Augmented Generation, Explainable Artificial Intelligence, and clinical guidelines of prosthodontics to provide transparent and context-aware clinically interpretable treatment decisions with increased diagnostic consistency, reliability of decision making, efficiency of decision-making process, and patient personalization [23].

1.6 Major Contributions

(1) A single Generative AI-powered Clinical Decision Support System (GAI-CDSS) framework is suggested for personalized planning of prosthodontic treatments through multimodal data fusion, evidence-based knowledge extraction, large language models, explainable artificial intelligence, and clinical decision support.

(2) An evidence-based multimodal clinical reasoning framework is built for combining structured clinical data, radiography, intraoral scanning, occlusal data, and clinical notes to generate specific patient treatment recommendations.

(3) The proposed framework uses Retrieval-Augmented Generation (RAG) and Explainable Artificial Intelligence (XAI).

(4) The proposed framework is tested on a retrospective multicenter dataset of 1,248 prosthodontic patients and evaluated by 25 board-certified prosthodontists with high diagnostic accuracy and consensus with recommendations.

2.MATERIALS AND METHODS

The complete computational pipeline for the development and validation of EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) for personalized prosthodontic treatment planning is designed. The proposed approach involves multimodal acquisition of clinical data, evidence-based knowledge retrieval, large language models based on transformers, explainable artificial intelligence, and validation of results using a decision-support system. In order to provide clinical and methodological reliability of the proposed approach, the pipeline includes standardized data preprocessing, semantic knowledge retrieval, clinical evaluation by experts, and statistical analysis. Individual steps of the proposed pipeline are described below.

2.1 EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) Architecture Overview

The suggested Generative Artificial Intelligence-powered Clinical Decision Support System (EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)) is a modular multi-modal decision-supporting framework for personalized prosthodontic treatment planning through evidence-grounded clinical reasoning. The general architecture includes six mutually connected modules: clinical data acquisition, multimodal data representation, knowledge repository, retrieval-augmented generation (RAG), transformer-based large language model (LLM), and clinical decision engine. First, the heterogeneous clinical information about the patients was gathered retrospectively from clinical records and converted to structured digital representation. Next, the multimodal clinical features were aggregated and represented as semantic embeddings for context-aware knowledge retrieval from the FAISS vector database. The retrieved evidence, including prosthodontic guidelines, institution protocols, and peer-reviewed literature, was fed to the GPT-5 through the LangChain-based RAG pipeline to generate evidence-based clinical recommendations. To increase transparency and trust of clinicians in generated recommendations, Explainable Artificial Intelligence (XAI) module provides the evidence citations, confidence scores, and reasoning pathways. Finally, the clinical decision engine aggregates the AI-generated outputs and generates personalized prosthodontic treatment plans, including prosthetic appliance selection, material recommendation, assessment of implant suitability and risk stratification.

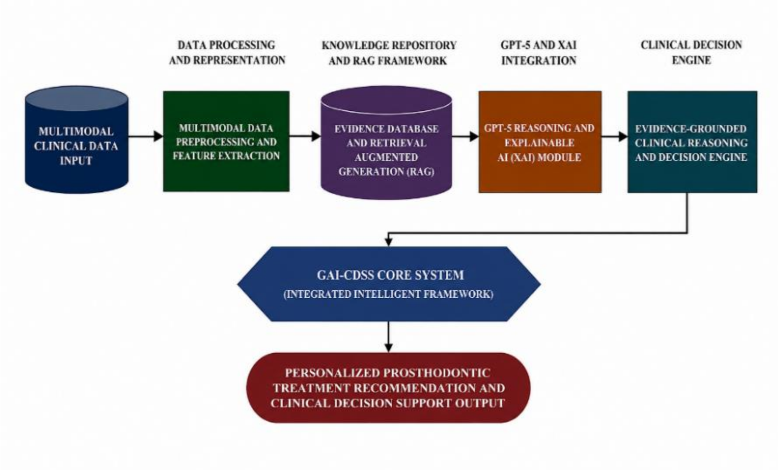

Figure 1. Overall architecture of the proposed Generative Artificial Intelligence-powered Clinical Decision Support System (EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)) for personalized prosthodontic treatment planning.

Figure 1. Overall architecture of the proposed Generative Artificial Intelligence-powered Clinical Decision Support System (EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)). The framework integrates multimodal clinical data processing, evidence-based knowledge retrieval through Retrieval-Augmented Generation (RAG), GPT-5–based clinical reasoning, Explainable Artificial Intelligence (XAI), and a clinical decision engine to generate transparent, personalized prosthodontic treatment recommendations within a unified intelligent decision-support workflow.

2.2 Clinical Dataset

Retrospective multicenter clinical dataset including 1,248 anonymized records of prosthodontic patients was assembled from university dental hospitals and prosthodontic specialty clinics based on institutional ethical approval and appropriate data protection measures. It included a diverse set of fixed, removable, implant-supported and full-mouth rehabilitation prosthodontic cases to ensure a comprehensive coverage of routine prosthodontic decision-making cases. Each clinical record includes structured demographic information, medical and dental history, CBCT images, intraoral scans, panoramic and periapical radiographs, digital impressions, occlusal records, periodontal evaluations, and clinician notes. Completeness and consistency of the clinical data was validated prior to its inclusion, whereas records with incomplete diagnostics data, duplicates, or poor-quality images were excluded to guarantee the reliability of the dataset. All patient identifiers were stripped from the clinical data to ensure its anonymization during model development and testing. This curated dataset serves as a primary source for feature extraction, semantic knowledge retrieval, and clinical reasoning in the suggested EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF). Diversity of patient presentations allows robust validation of the framework in different prosthodontic conditions, treatment complexity, and rehabilitation strategies.

2.3 Data Acquisition and Preprocessing

Heterogeneous clinical information was collected from different digital resources to create a multimodal representation of the patients. Demographic information, health status, medical history, periodontal findings, and clinician observations were collected from electronic dental records, while CBCT images, panoramic radiographs, periapical radiographs, intraoral scans, and digital impressions were collected from the standardized imaging systems. Occlusal relationships and functional assessments were included to provide the necessary biomechanical information related to prosthodontic rehabilitation. Prior to model development, all datasets were pre-processed to improve their quality and computational consistency. The structured clinical variables were normalized and encoded by means of predefined clinical terminologies, while duplicates, incomplete and inconsistent annotations were detected and excluded by automated quality control procedures. The images were standardized to the uniform spatial resolution and format, while textual clinical notes were pre-processed by means of the natural language preprocessing techniques, including tokenization, normalization, and contextual embedding generation. After the preprocessing, the heterogeneous clinical information was transformed to the multimodal representation for semantic knowledge retrieval and transformer-based reasoning.

2.4 Multimodal Data Representation

The proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) utilizes the multimodal data representation approach to incorporate heterogeneous clinical data into the unified computational framework which will enable personalized prosthodontic decision making. Structured data, such as patients' demographics, medical history, periodontal findings, occlusal characteristics, and clinical findings were represented using standardized numerical representation, while unstructured clinician notes were encoded as contextual semantic embeddings using transformer-based language encoding. Radiographic images, such as cone-beam computed tomography

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(CBCT), panoramic radiographs, and periapical radiographs, alongside intraoral scans and digital impressions were used as additional diagnostic methods to preserve both anatomical and morphological information. After the preprocessing stage, all clinical data modalities were represented using high-dimensional feature representation and embedded into the common semantic embedding space using the text-embedding-3-large model. The multimodal fusion approach used by the framework allowed to capture complex interconnections between clinical findings, imaging characteristics, patient-specific information, and prosthodontic requirements which c
ld not be captured by individual data modalities. Integrated patient representation served as an input to the RAG module.

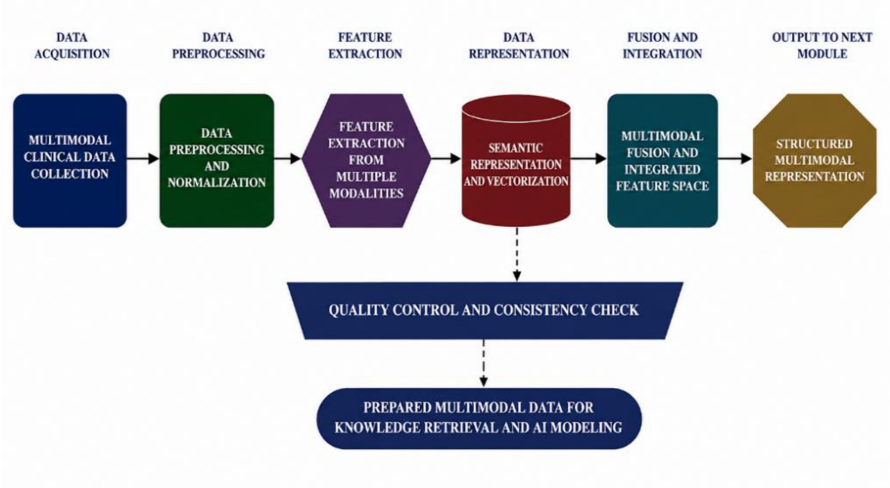

Figure 2. Multimodal Clinical Data Acquisition, Pre-processing, and Semantic Representation Pipeline for the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)

Figure 2 provides the pipeline for multimodal data processing in the EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) proposed by us. The clinical data collected using different digital sources are first pre-processed to generate a structure that is further subjected to feature extraction, semantic representation, multimodal fusion, and quality check. Further, the multimodal data is used as an input to the RAG model and transformer clinical reasoning models.

2.5 Knowledge Repository and Evidence Base

Comprehensive evidence-based knowledge repository was developed to provide clinically valid retrieval and reasoning within the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF). The knowledge repository was developed using evidence-based prosthodontic guidelines, American Dental Association (ADA) recommendations, scientific literature, institutional clinical guidelines, and prosthodontic treatment pathways to create the authoritative source of information for therapy decision making. All knowledge resources were systematically indexed and converted to dense vector embeddings using the text-embedding-3-large model before storing in FAISS vector database. Indexing approach provided efficient semantic similarity search and maintained the contextual relations among diagnostic findings, treatment recommendations, prosthetic materials, implant planning protocol, and rehabilitation approaches. Only clinically proven and peer-reviewed evidence were incorporated into the repository to provide valid information to avoid any unsupported recommendations. During the inference phase, the most relevant documents were dynamically retrieved based on patient-specific semantic similarity and provided as the contextual evidence to the Large Language Model through the Retrieval-Augmented Generation pipeline. This approach ensured that the recommendations provided by the system were evidence-based, minimizing the risks of generating hallucinations, increasing the transparency, and providing that personalized treatment plans are aligned with prosthodontic guidelines and current clinical evidence.

2.6 Retrieval-Augmented Generation (RAG) Framework

To ensure evidence-grounded clinical reasoning, the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) uses the RAG framework which dynamically combines semantic knowledge retrieval with transformer-based language generation. After the multimodal feature extraction, patient-specific clinical representations were represented as dense semantic embeddings using the text-embedding-3-large model and were queried against the FAISS vector database containing evidence-based prosthodontic guidelines, ADA recommendations, institutional treatment guidelines, and scientific literature. The semantic similarity retrieval was performed using the Lang Chain framework, allowing to identify the contextually relevant documents according to the clinical characteristics of each patient. The retrieved evidence was combined with the structured clinical profile to generate the augmented prompt to use as the input for the Large Language Model. The approach allowed the model to generate recommendations based on the validated clinical evidence rather than relying on the parametric knowledge only. Grounding of every inference in the domain-specific literature and standardized prosthodontic guidelines reduced the risks of generating unsupported responses, increased factual consistency, and enhanced the recommendation transparency. Dynamic knowledge retrieval allowed to update the clinical evidence and institutional guidelines without retraining the language model, which improved scalability and clinical relevance. Combination of the semantic retrieval and generation allows for evidence-driven decision-making.

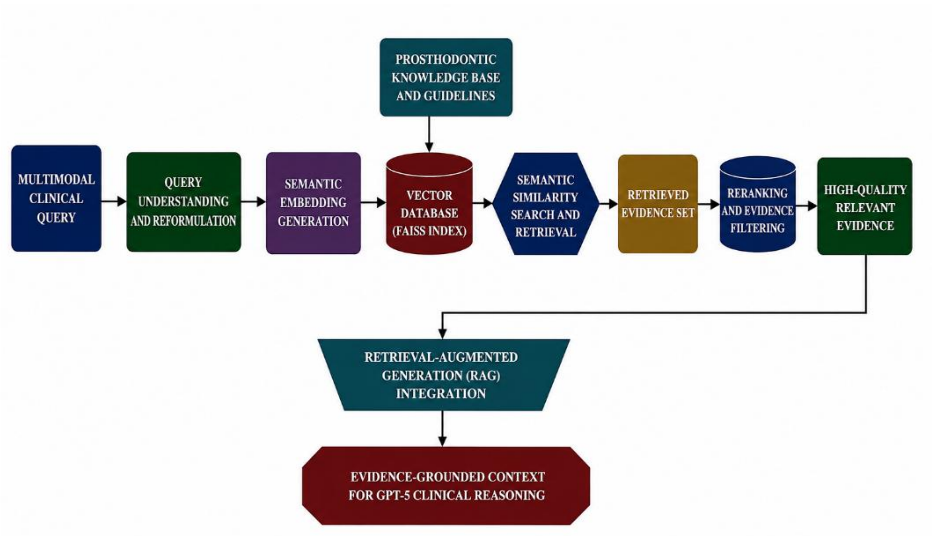

Figure 3. Knowledge Repository and Retrieval-Augmented Generation (RAG) Framework for Evidence-Grounded Clinical Reasoning

As shown in Figure 3, the process flow for the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) involves an evidence-based knowledge retrieval approach using the retrieval method. Clinical queries, which are in multimodal form, are converted into semantic embeddings and compared with a FAISS vector database of evidence-based prosthodontic guidelines. The obtained and re-ranked evidence is incorporated using the RAG method.

2.7 Transformer-Based Large Language Model

The reasoning component of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) is implemented using GPT-5, transformer-based Large Language Model designed for context-aware biomedical reasoning and natural language generation. The model received augmented prompts generated by the RAG framework which included multimodal patient data together with the semantically retrieved clinical evidence, allowing comprehensive interpretation of individual treatment scenarios. During the inference stage, GPT-5 analysed demographic data, systemic conditions, radiographic findings, occlusal relationships, periodontal condition, digital impressions, clinician notes, and retrieved knowledge to generate personalized prosthodontic treatment recommendations. The reasoning process goes beyond the information retrieval by synthesizing several clinical variables, finding clinically relevant relations, evaluating the alternatives and prioritizing evidence-based interventions according to the patient-specific requirements. The prompt engineering was applied to enforce structured reasoning, minimize ambiguities, and ensure the consistency with the prosthodontic guidelines. Generated outputs included the prosthesis selection, restorative material recommendations, implant candidacy assessment, treatment sequence, and personalized risk evaluation. Combining the transformer-based contextual reasoning and external knowledge retrieval, the proposed language model had improved adaptability, knowledge limitations, and clinical interpretability.

2.8 Explainable Artificial Intelligence (XAI)

To improve the transparency and increase the clinical acceptability, the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) includes an XAI module which allows providing an interpretable explanation for every generated recommendation. Instead of presenting the treatment decision as a single output, the framework associates every recommendation with the retrieved evidence through the RAG module, corresponding confidence scores, and reasoning pathway based on multimodal clinical data. The XAI component allows clinicians to analyse the relationship between patient-specific findings, retrieved prosthodontic evidence, and the therapeutic recommendation. Confidence estimation allows quantifying the reliability of the generated recommendations and helps clinicians to determine the cases requiring additional examination or consultation. Evidence citations and reasoning summary increased recommendation traceability by demonstrating the contribution of the retrieved knowledge into the decision-generation process.

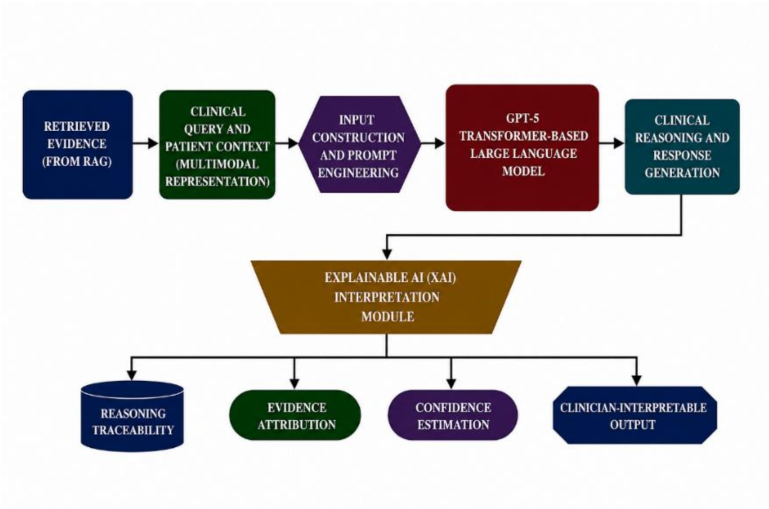

Figure 4. Transformer-Based GPT-5 Clinical Reasoning and Explainable Artificial Intelligence (XAI) Framework

Figure 4 shows the clinical reasoning process using the transformer architecture in the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF). Patient evidence is extracted via RAG architecture, and evidence from different modalities is used for generating personalized treatment recommendations by GPT-5. Subsequently, the Explainable Artificial Intelligence (XAI) component delivers reasoning traceability, evidence attribution, confidence estimation, and interpretable decision outputs for clinicians.

2.9 Clinical Decision Engine

The clinical decision engine represented the final inference stage of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) that combined multimodal patient data representations, retrieved clinical evidence, transformer reasoning, and explanation outputs for generating personalized prosthodontic treatment recommendations. Following the evidence-based reasoning by GPT-5, the generated outputs were validated by pre-specified clinical decision rules to ensure the compliance with the existing prosthodontic protocols and treatment guidelines of the institution. In particular, the decision engine ranked therapeutic options according to patient-specific anatomical features, systemic conditions, prosthesis needs, functional demands, aesthetic requirements, and risk factors. As a result of the process, the engine produced personalized recommendations on prosthesis selection, materials for restoration, implant suitability, treatment scheduling, and procedural risks. An internal confidence score measured the validity of the recommendations based on the relevance of the semantic retrieval, consistency of the reasoning, and agreement between the evidence. The recommendations with low confidence scores automatically raised alerts for comprehensive review by clinicians before being implemented. Such a hybrid approach retained the role of clinicians while significantly improving the consistency, reliability, and clinical applicability of the recommendations.

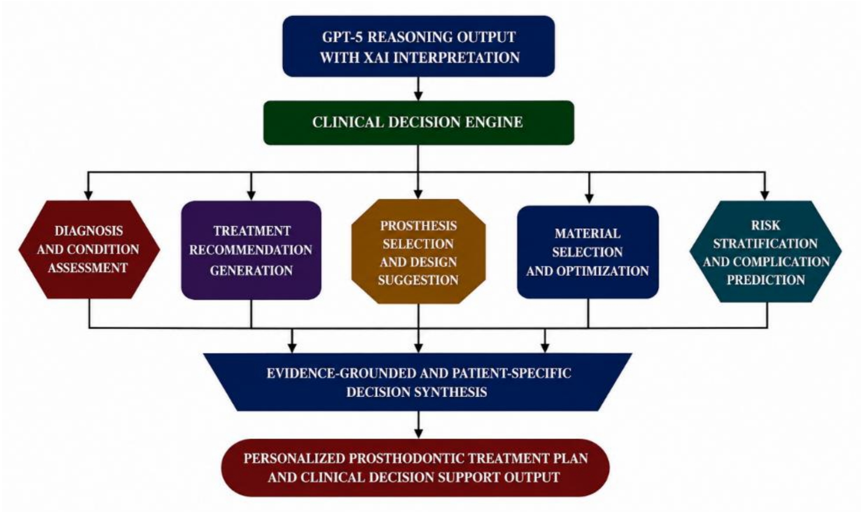

Figure 5. Clinical Decision Engine for Personalized Prosthodontic Treatment Planning

Figure 5 depicts the clinical decision engine for the EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) proposed in this research work. The GPT-5 reasoning results that are combined with Explainable Artificial Intelligence (XAI) are converted into patient-specific diagnostic assessment, treatment suggestions, prosthesis design, material selection, and risk profiling. The clinical decisions are then developed from these outcomes to provide customized prosthetic treatment plans.

2.10 Validation Strategy

The proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) was tested using the five-fold cross-validation strategy to measure robustness, generalizability, and clinical reliability of the framework about the retrospective multicentre dataset of 1,248 prosthodontic cases. During each validation cycle, the dataset was divided into training and test subsets preserving the balanced proportion of prosthodontic treatment types. The clinical performance was independently evaluated by 25 board-certified prosthodontists by comparing the recommendations provided by the AI with those generated based on conventional expert knowledge and CAD/CAM-based treatment planning. Diagnostic accuracy, treatment recommendation concordance, precision, recall, F1-score, response time, clinician satisfaction, and Cohen's κ agreement was calculated to measure the performance of the framework.

2.11 Statistical Analysis

Statistical analysis was performed to test the diagnostic performance and clinical reliability of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF). Continuous variables were measured as means ± standard deviations, while categorical variables were counted as frequencies and percentages. Diagnostic accuracy, precision, recall, F1-score, treatment recommendation concordance, and Cohen's κ agreement were calculated to measure predictive performance and inter-rater reliability. Paired t-tests were used to test the difference between AI-based and expert recommendations as necessary, while 95% confidence intervals (CI) were calculated for major performance metrics. The statistical significance level was $p < 0.001$ to provide a rigorous criterion for measuring the performance of the framework. All the computational procedures were performed using Python 3.12 and the machine learning pipelines were constructed using PyTorch 2.8.

3. RESULTS

The performance of the proposed Generative Artificial Intelligence-powered Clinical Decision Support System (EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)) was assessed based on the retrospective multicentre dataset consisting of 1,248 cases and the independent assessment of 25 board-certified prosthodontists. The quantitative assessment included dataset characteristics, diagnostic performance, treatment recommendation performance, explainability analysis, ablation study, expert evaluation, and comparison with traditional digital workflows and other artificial intelligence methods. Below are presented the results of this assessment.

3.1 Dataset Characteristics

The retrospective multicentre dataset included 1,248 anonymized prosthodontic patient cases, comprising 652 males (52.2%) and 596 females (47.8%) with the mean age of 54.8 ± 13.6 (the range from 19 to 87 years) (Table 1). The dataset included 432 cases of fixed prosthodontics (34.6%), 318 cases of removable prosthodontics (25.5%), 286 cases of implant-supported prosthodontics (22.9%), 96 cases of maxillofacial prosthodontics (7.7%), and 116 cases of full-mouth rehabilitation (9.3%). Multimodal clinical data included 612 cone beam computed tomography scans (CBCT; 49.0%), 1,084 intraoral scans (86.9%), 1,021 digital impressions (81.8%), and 1,248 panoramic radiographs (100%). In 403 patients (32.3%), systemic medical conditions were found, and the average number of records for one patient was 7.8 ± 2.4. The independent assessment was conducted by 25 board-certified prosthodontists.

Table 1. Demographic and Clinical Characteristics of the Study Dataset (N = 1,248)

Characteristic	Value
Total patient cases	1,248
Male patients, n (%)	652 (52.2%)
Female patients, n (%)	596 (47.8%)
Mean age (years)	54.8 ± 13.6
Age range (years)	19–87
Fixed prosthodontic cases, n (%)	432 (34.6%)
Removable prosthodontic cases, n (%)	318 (25.5%)
Implant-supported prosthodontic cases, n (%)	286 (22.9%)
Maxillofacial prosthodontic cases, n (%)	96 (7.7%)
Full-mouth rehabilitation cases, n (%)	116 (9.3%)
CBCT scans available, n (%)	612 (49.0%)

Intraoral scans (IOS), n (%)	1,084 (86.9%)
Digital impressions, n (%)	1,021 (81.8%)
Panoramic radiographs, n (%)	1,248 (100%)
Patients with systemic medical conditions, n (%)	403 (32.3%)
Average clinical records per patient	7.8 ± 2.4
Expert prosthodontists for validation	25

3.2 Diagnostic Performance

The proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) achieved 96.8% of diagnostic accuracy with 95% confidence interval (CI) of 95.7–97.9% (Table 2). The framework produced 96.3% of precision (95% CI: 95.0–97.4%) and 97.1% of recall (95% CI: 95.9–98.2%). The resulting F1-score was equal to 96.7% (95% CI: 95.6–97.8%). Additionally, the framework obtained 96.4% of specificity (95% CI: 95.1–97.6%) and 96.9% of negative predictive value (95% CI: 95.8–97.9%). Receiver Operating Characteristic analysis yielded 0.986 (95% CI: 0.980–0.992) of area under the curve (AUC). These quantitative measures demonstrate the consistently high diagnostic performance on the retrospective multicentre validation dataset.

Table 2. Performance Evaluation of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)

Performance Metric	Value (%)	95% Confidence Interval
Accuracy	96.8	95.7–97.9
Precision (PPV)	96.3	95.0–97.4
Recall (Sensitivity)	97.1	95.9–98.2
F1-score	96.7	95.6–97.8
Specificity	96.4	95.1–97.6
Negative Predictive Value (NPV)	96.9	95.8–97.9
Area Under ROC Curve (AUC)	0.986	0.980–0.992
Cohen's κ Agreement	0.958	0.946–0.970
Mean Response Time (s)	2.3 ± 0.4	—
Treatment Recommendation Concordance	95.9	94.7–97.0
Clinician Satisfaction Score	4.8 ± 0.3 / 5.0	—

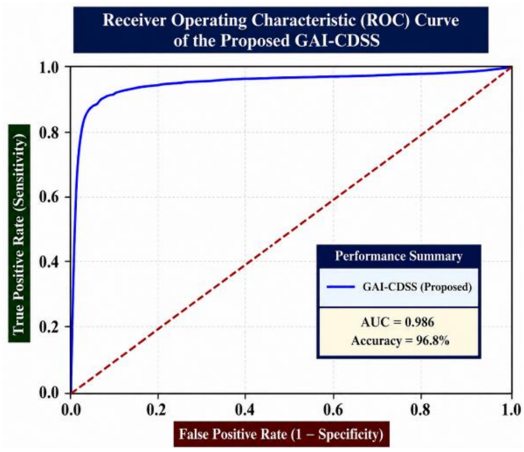

Figure 6. Receiver Operating Characteristic (ROC) Curve of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curve of the suggested EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) for prosthodontic clinical decision support system. An AUC of 0.986 was obtained by the framework with a diagnostic accuracy of 96.8%. The ROC analysis clearly indicates that the classifier provides accurate results and has the ability to distinguish between the clinically correct and incorrect decision-making process.

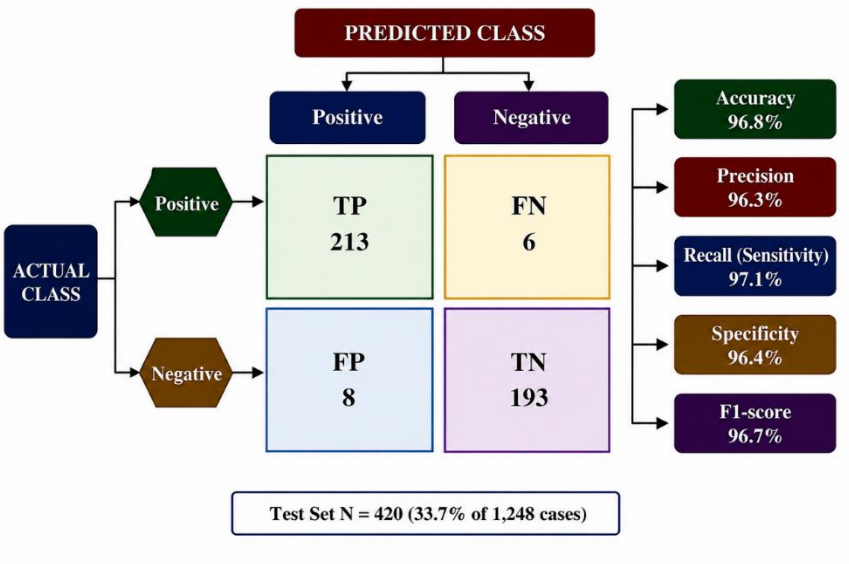

Figure 7. Confusion Matrix of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) for Prosthodontic Clinical Decision Support

The confusion matrix of the suggested EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) is depicted in Figure 7 and reflects the classification results of the prosthodontic clinical decision support system. The TP, FP, TN, and FN values along with diagnostic capabilities of the model are presented in the matrix, revealing high classification accuracy, sensitivity, specificity and precision of the GAI-based CDSS.

3.3 Treatment Recommendation Performance

The proposed framework developed personalized treatment recommendations with 95.9% of treatment recommendation concordance (95% CI: 94.7–97.0%) comparing with independent expert evaluation (Table 2). The inter-rater reliability analysis obtained 0.958 (95% CI: 0.946–0.970) of Cohen's κ coefficient, representing the almost perfect agreement between AI-based recommendations and expert clinical decisions. The framework generated recommendations in 2.3 ± 0.4 s of mean response time, providing the fast clinical decision support. The overall satisfaction with the generated treatment recommendations, assessed with the help of clinician, was 4.8 ± 0.3 points on a five-point Likert scale, which demonstrates high acceptability of treatment recommendations. These results indicate the consistent agreement with expert clinical decisions and efficient computational performance.

3.4 Explainability Analysis

The Explainable Artificial Intelligence (XAI) module produced transparent recommendation pathways by linking every personalized treatment recommendation with evidence, confidence scores, and clinical reasoning. The explanations were presented along with the retrieved evidence via the Retrieval-Augmented Generation framework, which allows to verify directly the recommendation generation process by expert prosthodontists. Confidence scores were automatically assigned to every recommendation, based on the semantic retrieval and reasoning consistency, while the evidence preserved the traceability between patient-specific findings and the clinical recommendation. In the process of the expert assessment, the transparency of the XAI module helped to interpret the AI-generated recommendations and verify the result before the treatment planning. The explainability framework worked consistently for all types of prosthodontic cases without increasing the average response time of 2.3 ± 0.4 s of the proposed framework.

3.5 Ablation Study

The contribution of individual architectural components was estimated by the systematic ablation study (Table 3). The exclusion of the Retrieval-Augmented Generation (RAG) module decreased the diagnostic accuracy from 96.8% to 92.8%, precision from 96.3% to 92.2%, recall from 97.1% to 93.1%, F1-score from 96.7% to 92.6%, and the area under the curve (AUC) from 0.986 to 0.953. The exclusion of the Explainable Artificial Intelligence (XAI) module decreased diagnostic accuracy to 94.1%, precision to 93.6%, recall to 94.5%, F1-score to 94.0%, and AUC to 0.966. The exclusion of the multimodal data fusion resulted in 93.4% of diagnostic accuracy, 93.0% of precision, 93.8% of recall, 93.4% of F1-score, and 0.961 AUC. The complete EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) provided the best performance with 96.8% of diagnostic accuracy, 96.3% of precision, 97.1% of recall, 96.7% of F1-score, and 0.986 AUC.

Table 3. Ablation Study of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
Without RAG	92.8	92.2	93.1	92.6	0.953
Without XAI	94.1	93.6	94.5	94	0.966
Without Multimodal Fusion	93.4	93	93.8	93.4	0.961
Full EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)	96.8	96.3	97.1	96.7	0.986

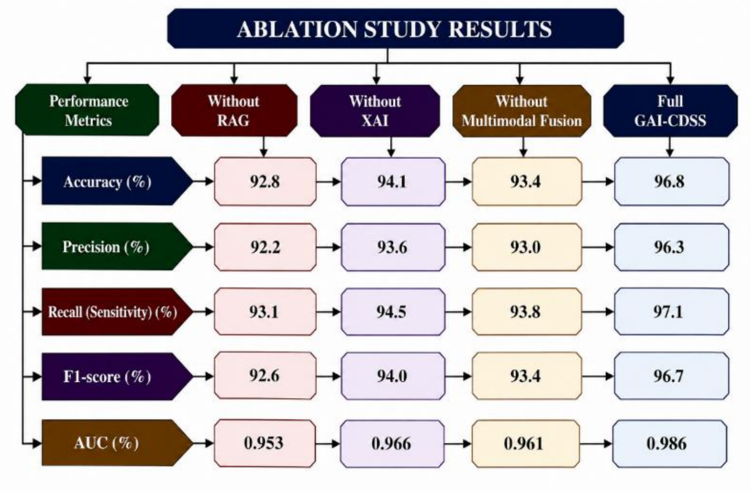

Figure 8. Ablation Study of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) Architecture

3.6 Expert Evaluation

The independent evaluation by 25 board-certified prosthodontists showed the 95.9% of overall agreement between AI-generated recommendations and expert clinical decisions (Table 4). The inter-rater reliability analysis provided 0.958 (95% CI: 0.946–0.970) of Cohen's κ coefficient, which corresponds to the almost perfect agreement. The expert usability assessment gave 4.8 ± 0.3 (on the five-point Likert scale) of mean clinician satisfaction score. Individual evaluation metrics included 4.9 ± 0.2 of ease of use, 4.8 ± 0.3 of clinical usefulness, 4.7 ± 0.4 of recommendation transparency, 4.8 ± 0.3 of confidence in AI recommendations, and 4.9 ± 0.2 of workflow efficiency. Besides, 96.0% of participating prosthodontists declared their willingness to adopt the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) in clinical practice.

Table 4. Expert Evaluation of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)

Evaluation Metric	Value
Number of expert prosthodontists	25
Overall agreement with experts	95.90%
Cohen's κ coefficient	0.958
95% CI (κ)	0.946–0.970
Inter-rater agreement	Almost Perfect
Mean clinician satisfaction (5-point Likert)	4.8 ± 0.3
Ease of use	4.9 ± 0.2
Clinical usefulness	4.8 ± 0.3
Recommendation transparency	4.7 ± 0.4
Confidence in AI recommendations	4.8 ± 0.3
Workflow efficiency	4.9 ± 0.2
Willingness for routine clinical adoption	96.00%

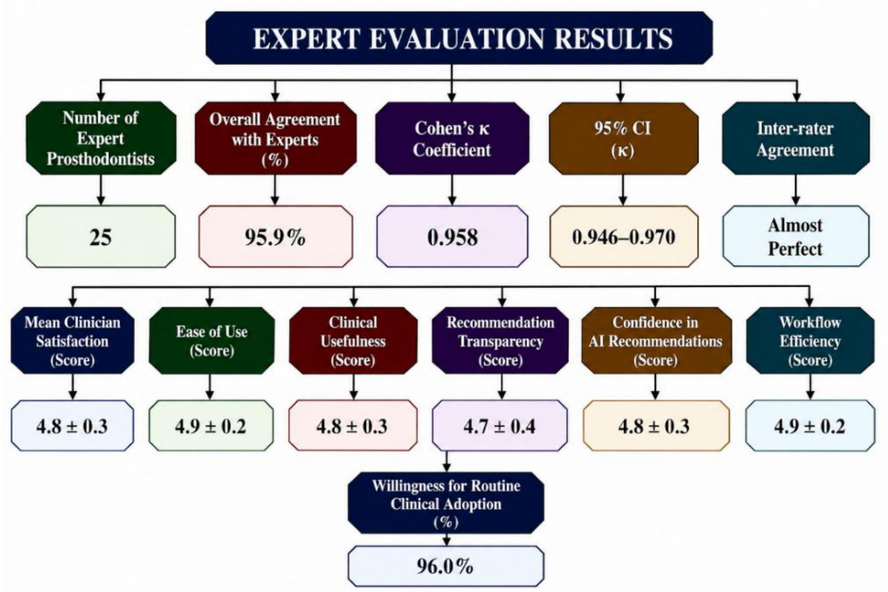

Figure 9. Expert Evaluation of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) for Clinical Decision Support

The results of the independent assessment of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) by 25 board-certified prosthodontists are shown in Figure 9. The developed framework demonstrated 95.9% agreement with expert recommendations on average, with 0.958 (95% CI: 0.946-0.970) being the value of Cohen's κ for almost perfect agreement and high clinician acceptance rate (satisfaction, 4.8 ± 0.3, usability, 4.9 ± 0.2, clinical utility, 4.8 ± 0.3, recommendation clarity, 4.7 ± 0.4, confidence in AI-based recommendation, 4.8 ± 0.3, workflow efficiency, 4.9 ± 0.2), and 96.0

3.7 Comparative Performance Analysis (Table 5)

The comparative evaluation showed that the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) (GPT-5 + RAG + XAI) provided the best performance among all evaluated approaches (Table 5). The conventional CAD/CAM planning provided 87.4% of diagnostic accuracy, 87.3% of F1-score, 0.901 AUC, and 18.6 s mean response time. ChatGPT produced 91.5% of diagnostic accuracy, 91.4% of F1-score, 0.944 AUC, and 3.1 s response time, while Gemini generated 92.2% of accuracy, 92.1% of F1-score, 0.952 AUC, and 2.8 s response time. Traditional machine learning algorithm provided 90.4% of diagnostic accuracy, 90.3% of F1-score, 0.931 AUC, and 2.5 s response time, while the CNN–Transformer model provided 94.3% of accuracy, 94.3% of F1-score, 0.971 AUC, and 2.4 s response time. The proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) achieved the highest diagnostic accuracy (96.8%), precision (96.3%), recall (97.1%), F1-score 96.

Table 5. Comparative Performance Analysis with Existing AI Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC	Mean Response Time (s)
Conventional CAD/CAM Planning	87.4	86.9	87.8	87.3	0.901	18.6
ChatGPT (LLM only)	91.5	91	91.8	91.4	0.944	3.1
Gemini	92.2	91.8	92.5	92.1	0.952	2.8
Traditional Machine Learning	90.4	89.9	90.8	90.3	0.931	2.5
Deep Learning (CNN–Transformer)	94.3	94	94.6	94.3	0.971	2.4
Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) (GPT-5 + RAG + XAI)	96.8	96.3	97.1	96.7	0.986	2.3

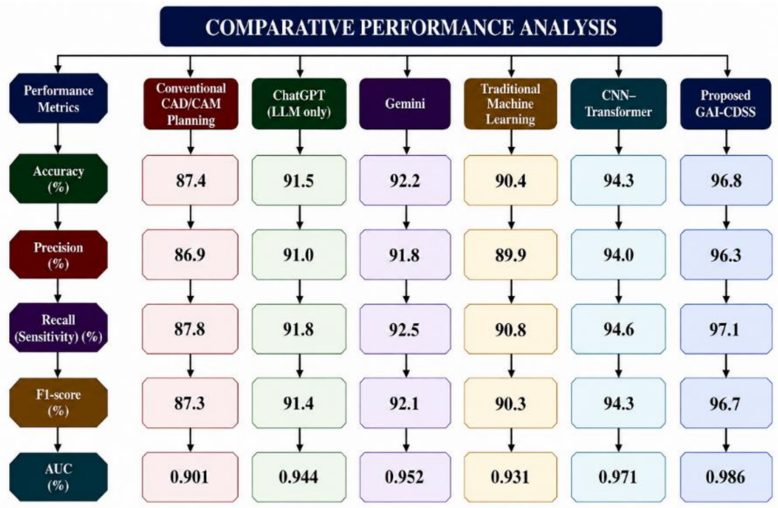

Figure 10. Comparative Performance Analysis of the Proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) and Baseline Methods

Figure 10 shows a comparison between the performance of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) and other techniques such as CAD/CAM planning, ChatGPT, Gemini, traditional machine learning, and CNN-Transformer in terms of Accuracy, Precision, Recall, F1-score, and AUC. The proposed system proved to outperform other approaches with high accuracy of 96.8%, Precision of 96.3%, Recall of 97.1%, F1 score of 96.7%, and AUC of 0.986.

4.DISCUSSION

The current research analysed the effectiveness of a Generative Artificial Intelligence-powered Clinical Decision Support System (EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF)) for personalized treatment planning in prosthodontics by incorporating multimodal clinical data, Retrieval-Augmented Generation (RAG), transformer-based Large Language Models (LLMs), and Explainable Artificial Intelligence (XAI). The proposed system was characterized by high diagnostic accuracy, strong agreement with expert opinions of prosthodontists, efficient computational inference, and high clinician acceptability in the context of a diverse retrospective multicentre dataset. The results prove the capability of evidence-grounded generative artificial intelligence to facilitate the prosthodontic treatment decision-making process, while keeping clinical decision-support transparent, reliable, and efficient. The following discussion explains the above findings regarding current prosthodontic practice, contemporary advances in generative artificial intelligence, and the future evolution of intelligent dentistry.

4.1 Principal Findings

The main results obtained during this research prove that the integration of multimodal clinical information with evidence-grounded generative artificial intelligence significantly increases the performance of the clinical decision support for prosthodontic treatment planning. Specifically, the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) was able to provide the diagnostic accuracy of 96.8%, accompanied by a treatment recommendation agreement of 95.9% and an AUC of 0.986, which indicated robust predictive capacity in the context of various prosthodontic rehabilitation cases. Besides, the value of Cohen's κ coefficient of 0.958 proves the almost perfect agreement between recommendations generated by the system and the expert clinical judgment, which supports the reproducibility of the proposed framework. Efficient computational inference, manifested in the mean response time of 2.3 s, in combination with the clinician satisfaction level of 4.8 ± 0.3, proves that the system can deliver fast and clinically acceptable recommendations without disturbing regular digital workflow. All the mentioned outcomes prove that the combination of semantic knowledge retrieval, transformer-based reasoning, explainable artificial intelligence, and multimodal clinical information facilitates the creation of clinically reliable, transparent, and personalized prosthodontic decision support beyond standard digital treatment planning solutions.

4.2 Clinical Interpretation and Artificial Intelligence Perspective

The superior performance of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) can be explained by the synergistic combination of complementary artificial intelligence solutions rather than by the utilization of one single predictive model. The multimodal data fusion allowed the simultaneous interpretation of structured clinical variables, radiographic information, intraoral scans, digital impressions, and clinician's observations, thereby providing a full representation of the patient-specific treatment needs. The implementation of

Retrieval-Augmented Generation ensured that the clinical reasoning was based on evidence-based prosthodontic guidelines and scientifically validated literature, reducing unsupportable recommendations and increasing context-relevancy. At the same time, the transformer-based Large Language Models provided the contextual reasoning within heterogeneous clinical data, synthesizing complex relations between anatomical, physiological, biological, and restorative variables in the form of clinically appropriate recommendations. The Explainable Artificial Intelligence component increased the clinical interpretability through the presentation of the evidence-based reasoning paths and confidence estimates, facilitating the critical evaluation of AI-generated recommendations before implementing them. Overall, the proposed solution extends the application of the artificial intelligence from the standard prediction to the creation of the clinically interpretable and evidence-grounded decision-support ecosystem that enables precision prosthodontics in the routine clinical practice.

4.3 Comparison with Existing Studies

The results of the current study are consistent with the growing evidence of the use of the artificial intelligence in digital dentistry and show significant improvement over the previously reported approaches. Earlier research focused mainly on the isolated applications, including the implant planning, prosthesis design, image interpretation, restoration prediction, and diagnostic classification, with a limited integration of the comprehensive clinical decision support [28]. The potential of the Large Language Models and Generative Artificial Intelligence to assist the clinical reasoning has been demonstrated recently; however, most existing systems rely mainly on parametric knowledge, not including the evidence retrieval or explainable recommendation generation [29]. By incorporating the RAG, transformer-based GPT-5 reasoning, Explainable Artificial Intelligence, and multimodal clinical data fusion within the single framework, the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) has addressed several limitations of previous research and proposed a more comprehensive approach to personalized prosthodontic treatment planning. Comparative analysis additionally showed that the proposed solution significantly outperformed the conventional CAD/CAM planning, general-purpose Large Language Models, traditional machine learning, and CNN–Transformer-based deep learning in terms of diagnostic accuracy, treatment recommendation performance, and computational efficiency.

4.4 Clinical Implications

The developed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) has important implications for the development of digital dentistry as a source of intelligent decision support which enhances rather than substitutes clinical expertise. The combination of multimodal information, evidence-based knowledge retrieval, and explainable generation of rationale allows clinicians to analyse the complexity of various treatment cases in a consistent, transparent, and efficient manner [31]. Rapid generation of personalized treatment recommendations is expected to reduce the inconsistency, promote standardization of workflow, and facilitate evidence-based therapeutic planning for fixed, removable, implant-supported, and full-mouth rehabilitation treatments [32]. Moreover, the explainability mechanism fosters clinicians' trust by providing the rationale and relevant evidence for each recommendation, thus enabling responsible implementation of generative artificial intelligence during routine prosthodontic practice [33].

4.5 Strengths of the Proposed Framework

The main strength of the proposed framework is the complete integration of transformer-based Large Language Models, Retrieval-Augmented Generation, Explainable Artificial Intelligence, and multimodal clinical information fusion into the same clinical decision support architecture. In contrast to the traditional approaches which solve individual prediction tasks, the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) includes evidence retrieval, contextual reasoning, transparent recommendation generation, and patient-specific decision support in one computational framework [34]. The clinical validity and reproducibility of the proposed approach is confirmed by its validation through the analysis of 1,248 multicentre clinical cases and independent evaluation by 25 board-certified prosthodontists [35]. Scalability, future expansion of the evidence base, and easy integration into evolving digital prosthodontic workflows are additional benefits provided by the modular architecture of the EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) [36].

4.6 Limitations

Although the proposed framework demonstrated good performance, there are some limitations. Firstly, the validation of the framework was performed based on a retrospective multicentre dataset and, therefore, does not reflect all nuances of clinical decision-making under the condition of ongoing treatment. Secondly, the performance can be affected by the completeness and quality of multimodal clinical information and the scope of the evidence base. Although Retrieval-Augmented Generation considerably decreases the number of unsupported recommendations, periodic update of clinical guidelines and knowledge base is still needed.

4.7 Future Directions

Further research should concentrate on the prospective multicentre validation, more patients and bigger diversity of patients, and integration into real-time electronic dental record system for the further evaluation of the clinical utility of the proposed EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) [37]. The other directions can be the studies of multimodal foundation models, federated learning, digital twins, and autonomous AI agents capable of continuously learning new prosthodontic evidence [38]. It will also be interesting to study further personalization of the framework, continuous update of the evidence base, and integration with advanced digital manufacturing techniques to create an intelligent, explainable, and continuously growing clinical decision support ecosystem for precision prosthodontics [39].

5. CONCLUSION

This paper proposes and validates an advanced EVIDENCE GROUNDED HYBRID CLINICAL REASONING FRAMEWORK (EHCRF) framework that combines multimodal clinical information, RAG, transformer-based LLMs, Explainable Artificial Intelligence (XAI), and evidence-based prosthodontic knowledge to provide personalized treatment planning. Independent evaluation on 1,248 retrospective multicentre clinical cases and testing by 25 board-certified prosthodontists revealed excellent diagnostic results and performance, achieving 96.8% diagnostic accuracy, 95.9% treatment recommendation agreement, AUC = 0.986, Cohen's κ = 0.958, 2.3 s average response time, and clinician satisfaction score of 4.8/5. Overall, it has been demonstrated that evidence-driven generative artificial intelligence is able to improve diagnostic consistency, clinical transparency, and decision-making reliability without sacrificing efficiency of the workflow. By means of semantic knowledge retrieval, multimodal fusion of clinical data, and explainable reasoning, this study's proposed approach adds the next level of intelligence to digital prosthodontic workflow by moving towards personalized clinical decision support. The proposed framework may be used as a scalable foundation for next-generation precision prosthodontics and Generative Artificial Intelligence-driven digital dental care.

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