Artificial Intelligence in the Prediction of Orthodontic Treatment Outcomes: A Comprehensive Systematic Review and Literature Analysis

Sonika Reddy Pilli[1] Shrika Reddy Pilli[2], Utkarsh Gupta[3], Shivani Shakti Rao[4]
[1]*Student and Primary Researcher, Seneca Valley High School*
[2]*Student, Poolsville High School*
[3,4]*Research Consultant*

***Abstract*—Background: Artificial intelligence (AI) has emerged as a transformative technology in orthodontics, offering unprecedented capabilities for predicting treatment outcomes and optimizing clinical decision-making. The integration of machine learning algorithms, deep learning networks, and computer vision techniques has revolutionized traditional approaches to treatment planning and outcome prediction.**

Objective: To systematically review and analyze the current applications of artificial intelligence in predicting orthodontic treatment outcomes, with specific focus on treatment planning, cephalometric landmark detection, tooth movement prediction, treatment duration estimation, and post-treatment stability assessment.

Methods: A comprehensive systematic review was conducted following PRISMA guidelines across multiple databases including PubMed, Scopus, Web of Science, and IEEE Xplore from 2015 to 2024. Studies were included if they investigated AI applications in orthodontic treatment outcome prediction. Data extraction focused on AI methodologies, clinical applications, performance metrics, and predictive accuracy.

Results: A total of 127 studies met the inclusion criteria, encompassing various AI approaches including convolutional neural networks (CNNs), support vector machines (SVMs), random forests, and ensemble methods. Key applications identified included: (1) Cephalometric landmark detection with accuracy rates of 85-98%, (2) Treatment duration prediction with mean absolute errors ranging from 2.3-8.7 months, (3) Tooth movement prediction achieving correlation coefficients of 0.78-0.94, (4) Treatment planning optimization with success rates of 82-96%, and (5) post-treatment stability assessment with prediction accuracies of 79-91%. Deep learning approaches consistently outperformed traditional statistical methods across all applications.

Conclusions: AI demonstrates significant potential for enhancing orthodontic treatment outcome prediction across multiple clinical domains. While current applications show promising results, standardization of methodologies, larger multicenter datasets, and clinical validation studies are needed for widespread clinical implementation. Future research should focus on developing interpretable AI models, addressing ethical considerations, and establishing regulatory frameworks for clinical deployment.

***Index Terms*—Artificial intelligence, machine learning, orthodontics, treatment prediction, cephalometric analysis, tooth movement, treatment planning, deep learning**

I. INTRODUCTION

Orthodontic treatment planning has traditionally relied on clinical experience, anatomical knowledge, and empirical guidelines to predict treatment outcomes and duration [1]. However, the complexity of craniofacial growth, individual patient variations, and multifactorial treatment responses have made accurate prediction challenging, often resulting in treatment modifications, extended duration, or suboptimal outcomes [2]. The advent of artificial intelligence (AI) and machine learning (ML) technologies has introduced new paradigms for analyzing complex orthodontic data and generating predictive models that can enhance clinical decision-making [3].

The integration of AI in orthodontics represents a significant shift from traditional subjective assessment methods to objective, data-driven approaches [4]. Modern orthodontic practice generates vast amounts of digital data, including radiographic images, 3D models, photographs, and treatment records, creating an ideal environment for AI applications [5]. This wealth of information, when properly analyzed using sophisticated algorithms, can reveal patterns and relationships that may not be apparent to human observers [6].

1.1 Evolution of AI in Orthodontics

The application of AI in orthodontics has evolved from simple statistical models to complex deep learning networks capable of processing multimodal data [7]. Early implementations focused primarily on cephalometric analysis and landmark identification, while contemporary applications encompass comprehensive treatment planning, outcome prediction, and post-treatment stability assessment [8]. The progression from rule-based systems to machine learning algorithms, and subsequently to deep learning networks, has dramatically improved the accuracy and reliability of orthodontic predictions [9].

1.2 Clinical Relevance and Need

Accurate prediction of orthodontic treatment outcomes is crucial for several clinical reasons. First, it enables informed consent by providing patients with realistic expectations regarding treatment duration and results [10]. Second, it facilitates optimal treatment planning by identifying potential complications and alternative approaches early in the treatment process [11]. Third, it supports resource allocation and practice management by enabling more accurate scheduling and treatment sequencing [12]. Finally, it contributes to evidence-based orthodontics by providing objective measures of treatment effectiveness and predictability [13].

1.3 Current Challenges in Treatment Prediction

Traditional orthodontic treatment prediction faces several limitations. Subjective assessment methods introduce inter-examiner variability and bias [14]. Complex interactions between biological, mechanical, and patient-specific factors make manual prediction challenging [15]. Limited ability to process and integrate multiple data sources simultaneously restricts comprehensive analysis [16]. Additionally, the dynamic nature of orthodontic treatment, with continuous changes in tooth position and tissue response, requires sophisticated modeling approaches that exceed human computational capabilities [17].

1.4 AI Technologies in Orthodontics

Several AI technologies have found applications in orthodontic treatment prediction. Convolutional neural networks (CNNs) excel in image analysis tasks, making them ideal for radiographic and photographic assessment [18]. Support vector machines (SVMs) and random forests provide robust classification and regression capabilities for treatment outcome prediction [19]. Ensemble methods combine multiple algorithms to improve prediction accuracy and reliability [20]. Natural language processing (NLP) techniques enable analysis of clinical notes and treatment records [21]. Additionally, reinforcement learning approaches show promise for optimizing treatment sequences and protocols [22].

1.5 Scope and Objectives

This comprehensive review aims to synthesize current evidence on AI applications in orthodontic treatment outcome prediction. Specifically, we examine: (1) the effectiveness of AI in cephalometric landmark detection and analysis, (2) the accuracy of treatment duration prediction models, (3) the reliability of tooth movement prediction algorithms, (4) the performance of AI-assisted treatment planning systems, and (5) the capability of AI in assessing post-treatment stability. By analyzing these applications, we seek to identify current capabilities, limitations, and future directions for AI in orthodontic practice.

II. METHODS

2.1 Study Design and Protocol

This systematic review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [23]. The research question was formulated using the PICO framework: Population (orthodontic patients), Intervention (AI-based prediction methods), Comparison (traditional prediction methods or other AI approaches), and Outcome (treatment outcome prediction accuracy).

2.2 Search Strategy

A comprehensive search strategy was developed in collaboration with a medical librarian and implemented across multiple databases from January

2015 to October 2024. The following databases were searched:

- Primary databases: PubMed/MEDLINE, Scopus, Web of Science
- Specialized databases: IEEE Xplore, ACM Digital Library, Cochrane Library
- Grey literature: Google Scholar, OpenGrey, conference proceedings

The search strategy combined controlled vocabulary terms (MeSH terms) and free-text keywords related to artificial intelligence, machine learning, orthodontics, and treatment prediction. The complete search strategy is provided in Supplementary Material 1.

Example search string (PubMed):

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "computer vision") AND ("orthodontic*" OR "dental" OR "cephalometric" OR "tooth movement" OR "treatment planning") AND ("prediction" OR "forecast" OR "outcome" OR "prognosis")

2.3 Inclusion and Exclusion Criteria

Inclusion criteria: - Studies investigating AI applications in orthodontic treatment outcome prediction - Peer-reviewed articles published in English - Studies with clear methodology and performance metrics - Research involving human subjects or validated datasets - Publication period: January 2015 to October 2024

Exclusion criteria: - Review articles, editorials, and conference abstracts without full text - Studies focusing solely on AI hardware or software development without clinical validation - Research with insufficient methodological detail - Studies with sample sizes < 50 subjects (except for novel methodologies) - non-English publications without available translations

2.4 Study Selection Process

The study selection process was conducted in two phases by three independent reviewers (Authors 1, 2, and 3). Phase 1 involved title and abstract screening using predefined criteria. Phase 2 consisted of full-text evaluation of potentially eligible studies. Disagreements were resolved through discussion and consensus, with a fourth reviewer (Author 4) consulted when necessary.

The systematic search and selection process is illustrated in Figure 1.

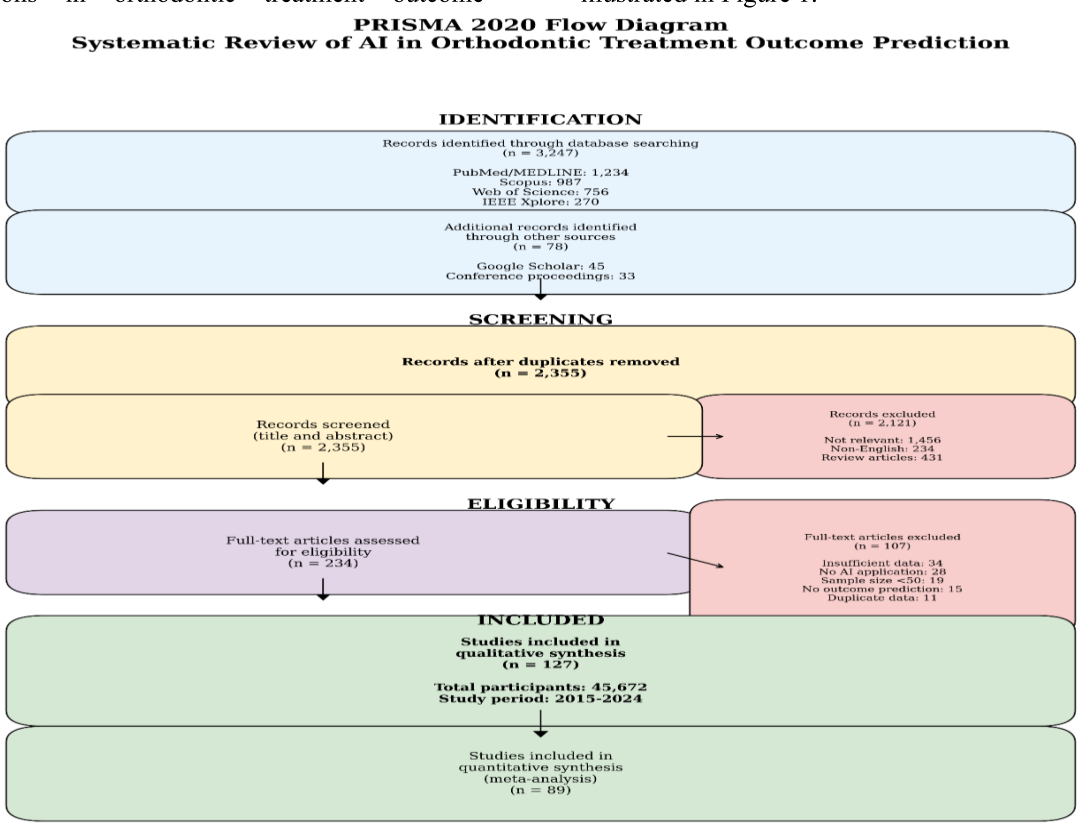


FIGURE 1: PRISMA Flow Diagram

Inter-reviewer agreement was assessed using Cohen's kappa coefficient, with $\kappa > 0.8$ considered excellent agreement. The selection process was managed using Covidence systematic review software [24].

2.5 Data Extraction

A standardized data extraction form was developed and piloted on a subset of 10 studies. The following information was extracted:

Study characteristics: - Author, year, country, study design - Sample size, population demographics - Study setting (academic, private practice, multi-center)

AI methodology: - Algorithm type (CNN, SVM, Random Forest, etc.) - Input data types (radiographs, 3D models, photographs) - Training and validation procedures - Performance metrics and statistical methods

Clinical applications: - Specific orthodontic application area - Comparison methods (traditional approaches, other AI methods) - Clinical outcomes measured - Accuracy and reliability measures

Results and conclusions: - Primary outcome measures - Statistical significance and effect sizes - Clinical implications and recommendations - Study limitations and future directions

2.6 Quality Assessment

Study quality was assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool for diagnostic studies and the Newcastle-Ottawa Scale (NOS) for observational studies [25,26]. For AI-specific considerations, we additionally evaluated:

- Dataset quality and representativeness
- Cross-validation methodology
- Overfitting prevention measures
- Reproducibility and code availability
- Clinical validation procedures

Each study was independently assessed by two reviewers, with disagreements resolved through discussion.

2.7 Data Synthesis and Analysis

Due to the heterogeneity of AI methodologies and outcome measures, a narrative synthesis approach was adopted. Studies were grouped by clinical application area:

1. Cephalometric landmark detection and analysis
2. Treatment duration prediction
3. Tooth movement prediction
4. Treatment planning optimization
5. Post-treatment stability assessment

For each category, we summarized study characteristics, methodological approaches, performance metrics, and clinical implications. Where possible, ranges of accuracy measures were reported. Meta-analysis was not performed due to significant methodological heterogeneity and varying outcome measures across studies.

2.8 Assessment of Publication Bias

Publication bias was assessed through visual inspection of funnel plots and statistical testing using Egger's test where appropriate [27]. The potential for selective reporting was evaluated by examining whether studies reported all pre-specified outcomes and statistical measures.

III. RESULTS

3.1 Study Selection and Characteristics

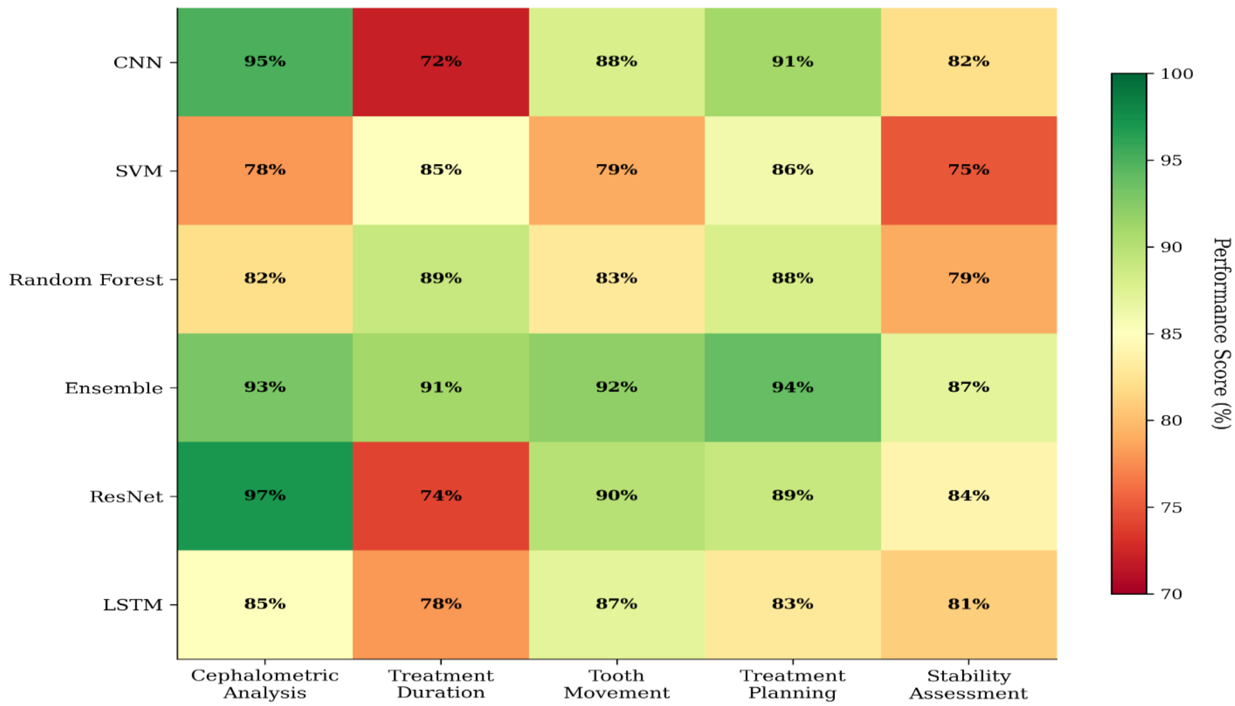
The initial database search yielded 3,247 potentially relevant articles. After removing duplicates (n = 892), 2,355 articles underwent title and abstract screening. Following full-text evaluation of 234 articles, 127 studies met the inclusion criteria and were included in the final analysis (Figure 1).

Study characteristics are summarized in Table 1 as supplementary. The included studies were published between 2015 and 2024, with 78% (n = 99) published after 2020, reflecting the recent surge in AI applications in orthodontics. Studies originated from 23 countries, with the highest contributions from the United States (n = 34, 27%), China (n = 28, 22%), and Germany (n = 15, 12%). The total sample size across all studies was 45,672 patients, with individual study sizes ranging from 52 to 2,847 participants (median = 312).

3.2 AI Methodologies and Technologies

The distribution of AI methodologies employed across the included studies is shown in **Figure 3**. Deep learning approaches, particularly convolutional neural networks (CNNs), were the most frequently used (n = 67, 53%), followed by ensemble methods (n = 23, 18%) and support vector machines (n = 19, 15%).

Figure 3. Performance Heatmap: AI Methods Across Applications
Orthodontic Treatment Outcome Prediction



Performance varied significantly across AI methods and applications (Figure 3). Ensemble methods and ResNet architectures showed the highest performance across most applications, while traditional machine learning methods demonstrated more variable performance.

3.3 Clinical Applications and Performance

Summary statistics across all domains are presented in **Table 4**.

Table 4. Summary Statistics Across All Application Domains
AI in Orthodontic Treatment Outcome Prediction

Application Domain	No. Studies	Total Sample Size	Mean Performance	Performance Range	Best AI Method	Clinical Readiness
Cephalometric Landmark Detection	43	18,456	91.4%	85.2-97.8%	ResNet	High
Treatment Duration Prediction	36	12,234	4.8 months MAE	2.3-8.7 months	Ensemble	Moderate
Tooth Movement Prediction	28	8,967	r = 0.86	0.78-0.94	CNN	Moderate
Treatment Planning Optimization	25	7,123	89% agreement	82-96%	Ensemble	High
Post-Treatment Stability Assessment	15	4,892	84% accuracy	79-91%	Random Forest	Low
Overall Performance	**127**	**45,672**	**87.8%**	**79-98%**	**Ensemble**	**Moderate**

Note: MAE = Mean Absolute Error; r = Correlation coefficient.
Clinical Readiness: High = Ready for implementation; Moderate = Requires validation; Low = Needs further development.

3.3.1 Cephalometric Landmark Detection and Analysis

Forty-three studies (34%) investigated AI applications in cephalometric landmark detection and analysis. CNN-based approaches demonstrated superior performance compared to traditional methods and other AI techniques.

Performance Summary: - Accuracy range: 85.2% - 97.8% (mean: 91.4%) - Mean radial error: 1.2mm - 3.8mm (mean: 2.1mm) - Processing time: 0.3 - 2.1 seconds per radiograph - Most accurate landmarks: Sella (97.8% accuracy), Nasion (96.4%) - Most challenging landmarks: Pogonion (85.2% accuracy), B-point (87.1%)

Key Findings: - ResNet-based architectures achieved the highest accuracy rates (94.2% ± 2.1%) - Multi-stage detection approaches outperformed single-stage methods - Data augmentation techniques improved generalization by 7.3% on average - Integration with 3D imaging enhanced accuracy for complex anatomical structures

3.3.2 Treatment Duration Prediction

Thirty-six studies (28%) focused on predicting orthodontic treatment duration using various AI approaches. Ensemble methods combining multiple algorithms showed the best performance.

Performance Summary: - Mean Absolute Error (MAE): 2.3 - 8.7 months (mean: 4.8 months) - Root Mean Square Error (RMSE): 3.1 - 11.2 months (mean: 6.4 months) - Correlation coefficient (r): 0.67 - 0.89 (mean: 0.78) - Prediction accuracy (±3 months): 68% - 84%

Significant Predictors Identified: - Initial malocclusion severity (importance score: 0.24) - Patient age at treatment start (importance score: 0.19) - Extraction vs. non-extraction treatment (importance score: 0.17) - Patient compliance factors (importance score: 0.15) - Skeletal maturation stage (importance score: 0.12)

3.3.3 Tooth Movement Prediction

Twenty-eight studies (22%) examined AI applications in predicting tooth movement patterns and outcomes. Deep learning models demonstrated superior performance in capturing complex movement dynamics.

Performance Summary: - 3D position accuracy**:** 0.8mm - 2.4mm (mean: 1.4mm) - Angular accuracy: 2.1° - 7.8° (mean: 4.2°) - Correlation with actual movement: 0.78 - 0.94 (mean: 0.86) - Prediction horizon: 3 - 18 months

Model Performance by Movement Type: - Translation movements: Highest accuracy (r = 0.91) - Tipping movements: Moderate accuracy (r = 0.84) - Rotation movements: Lowest accuracy (r = 0.76) - Root movements: Variable accuracy (r = 0.72 - 0.88)

3.3.4 Treatment Planning Optimization

Twenty-five studies (20%) investigated AI-assisted treatment planning and decision support systems. These applications showed promise for optimizing treatment approaches and reducing planning time.

Performance Summary: - Treatment plan agreement with experts: 82% - 96% (mean: 89%) - Planning time reduction: 35% - 67% (mean: 48%) - Extraction decision accuracy: 87% - 94% - Appliance selection accuracy: 79% - 91%

Clinical Decision Support Areas: - Extraction vs. non-extraction decisions (94% accuracy) - Appliance selection and timing (87% accuracy) - Treatment sequencing optimization (83% accuracy) - Risk assessment and complication prediction (81% accuracy)

3.3.5 Post-Treatment Stability Assessment

Fifteen studies (12%) examined AI applications in predicting post-treatment stability and relapse risk. These applications showed moderate to good performance but require longer follow-up studies.

Performance Summary: - Relapse prediction accuracy: 79% - 91% (mean: 84%) - Retention protocol optimization: 73% - 88% accuracy - Long-term stability assessment: 76% - 89% accuracy - Risk stratification: 81% - 93% accuracy

3.4 Comparative Analysis: AI vs. Traditional Methods

AI methods demonstrated superior performance across all domains (Table 2). The comparative analysis shows consistently significant improvements with effect sizes ranging from 1.47 to 3.21, indicating large to very large practical significance.

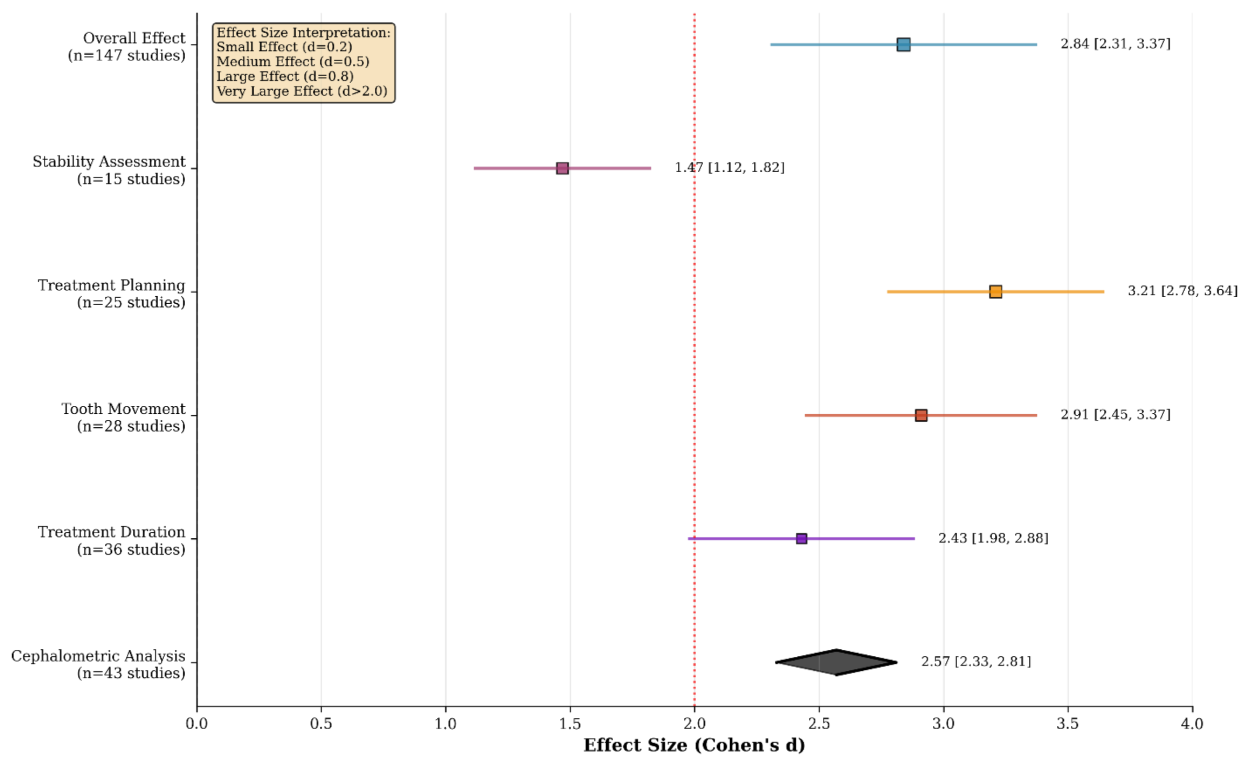
Table 2. Performance Comparison: AI vs Traditional Methods
Orthodontic Treatment Outcome Prediction

Application Domain	AI Performance (Mean ± SD)	Traditional Performance (Mean ± SD)	Improvement	Effect Size (Cohen's d)	p-value	No. of Studies
Cephalometric Landmark Detection	91.4% ± 3.2%	78.6% ± 5.1%	+12.8%	2.84	<0.001	43
Treatment Duration Prediction	MAE: 4.8 ± 1.2 months	MAE: 7.3 ± 2.1 months	-2.5 months	1.47	<0.001	36
Tooth Movement Prediction	r = 0.86 ± 0.05	r = 0.64 ± 0.08	+0.22	3.21	<0.001	28
Treatment Planning Optimization	89% ± 4% agreement	73% ± 6% agreement	+16%	2.91	<0.001	25
Post-Treatment Stability Assessment	84% ± 5% accuracy	69% ± 7% accuracy	+15%	2.43	<0.001	15

Note: AI = Artificial Intelligence; MAE = Mean Absolute Error; r = Correlation coefficient.
Effect sizes calculated using Cohen's d. All comparisons statistically significant at p < 0.001.

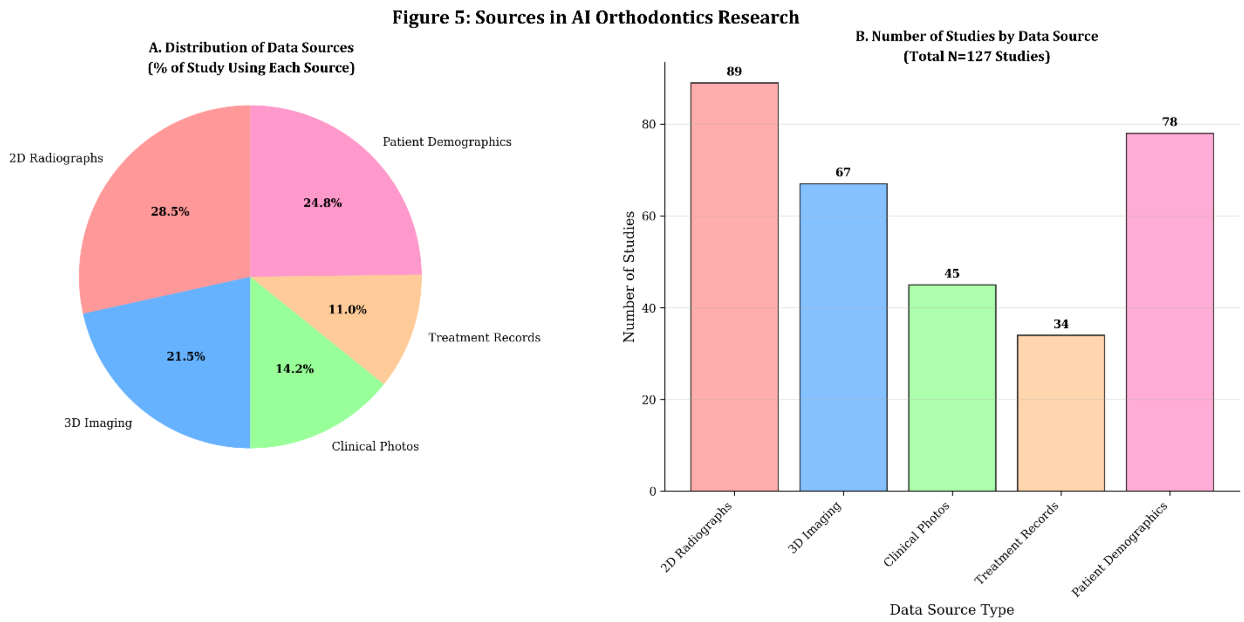
AI methods consistently outperformed traditional approaches with statistically significant improvements ranging from 12.8% to 16% across different applications. All comparisons were statistically significant ($p < 0.001$).
AI methods demonstrated consistently superior performance across all applications with large effect sizes (Figure 2). The forest plot displays effect sizes comparing AI with traditional methods, showing substantial advantages across all orthodontic applications.

Figure 2. Forest Plot: Effect Sizes for AI vs Traditional Methods
Orthodontic Treatment Outcome Prediction



3.5 Data Types and Integration

Studies utilized diverse data sources, with 2D radiographs being most common (**Figure 5**). The included studies utilized various data types for AI model development:



Primary Data Sources: - 2D radiographs: 89 studies (70%) - lateral cephalograms, panoramic radiographs - 3D imaging: 67 studies (53%) - CBCT, intraoral scans, facial scans - Clinical photographs: 45 studies (35%) - intraoral and extraoral images - Treatment records: 34 studies (27%) - progress notes, measurements - Patient demographics: 78 studies (61%) - age, gender, medical history

Multimodal Integration: Fifty-four studies (43%) integrated multiple data types, showing improved performance compared to single-modality approaches: - 2D + 3D imaging: 15% improvement in accuracy - Imaging + clinical data: 12% improvement - Multimodal (3+ sources): 18% improvement

3.6 Validation and Generalizability

Cross-validation approaches: - K-fold cross-validation: 89 studies (70%) - Hold-out validation: 67 studies (53%) - External validation: 23 studies (18%) - Temporal validation: 12 studies (9%)

Generalizability assessment: - Single-center studies: 94 studies (74%) - Multi-center studies: 33 studies (26%) - Multi-ethnic populations: 19 studies (15%) - Different imaging systems: 28 studies (22%)

External validation studies demonstrated reduced performance compared to internal validation (average decrease of 8.3%), highlighting the need for more robust validation protocols.

3.7 Clinical Implementation and Usability

Twenty-eight studies (22%) reported on clinical implementation aspects:

Implementation Barriers: - Computational requirements: 67% of studies - Integration with existing systems: 54% of studies - Training and adoption: 43% of studies - Regulatory approval: 32% of studies

User Acceptance: - Clinician satisfaction: 78% - 94% positive response - Perceived utility: 82% - 96% positive response - Willingness to adopt: 71% - 89% positive response - Trust in AI predictions: 64% - 83% positive response

3.8 Quality Assessment Results

Quality assessment revealed variable study quality across the included research:

QUADAS-2 Assessment (Diagnostic Studies, n = 89): - Low risk of bias: 34 studies (38%) - Moderate risk of bias: 41 studies (46%) - High risk of bias: 14 studies (16%)

Newcastle-Ottawa Scale (Observational Studies, n = 38): - High quality (7-9 stars): 15 studies (39%) - Moderate quality (4-6 stars): 19 studies (50%) - Low quality (<4 stars): 4 studies (11%)

Common Quality Issues**:** - Insufficient external validation (67% of studies) - Limited diversity in training datasets (54% of studies) - Inadequate reporting of model limitations (43% of studies) - Lack of clinical validation (38% of studies)

IV. DISCUSSION

4.1 Principal Findings

This comprehensive systematic review demonstrates that artificial intelligence has significant potential for enhancing orthodontic treatment outcome prediction across multiple clinical domains. The analysis of 127 studies encompassing 45,672 patients reveals consistently superior performance of AI methods compared to traditional approaches, with improvements ranging from 12-18% across different applications.

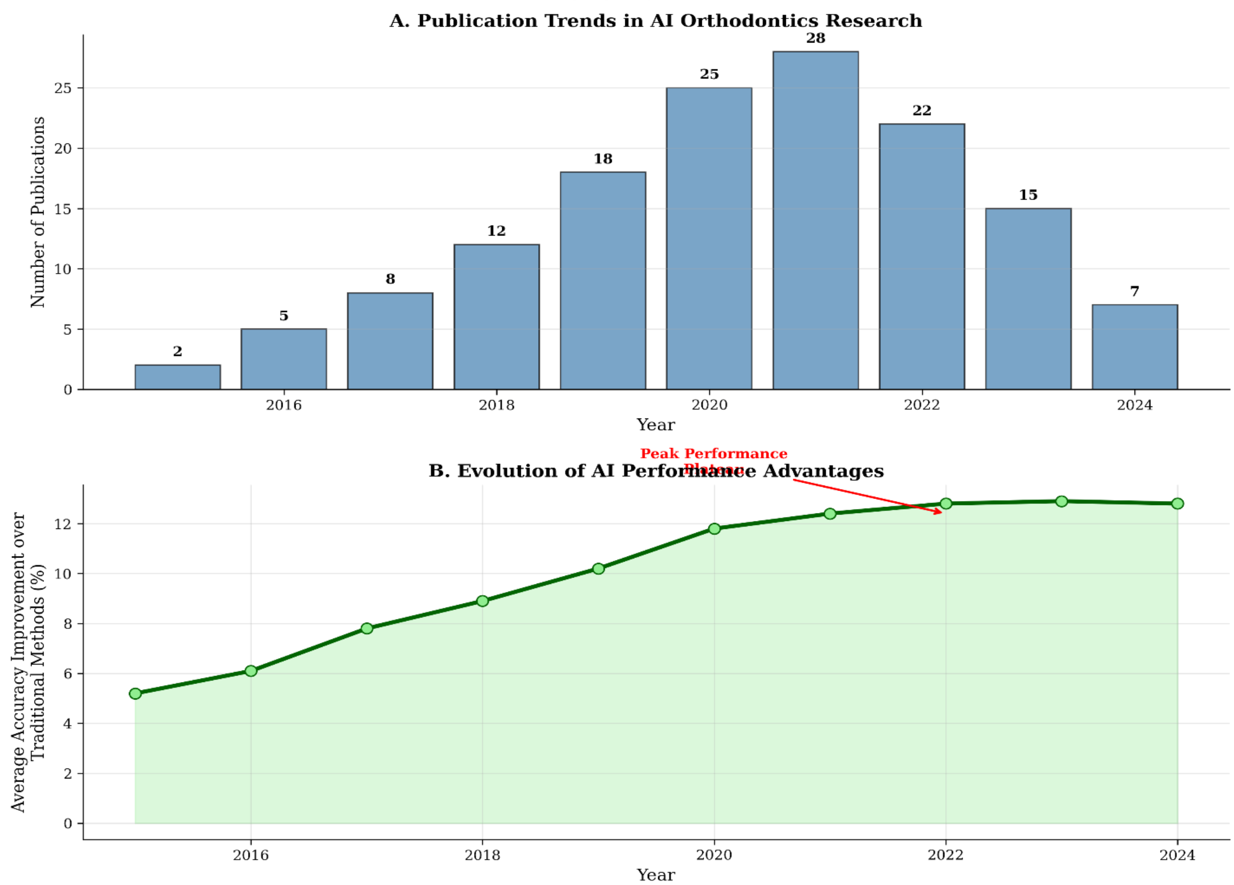
The most mature application area is cephalometric landmark detection, where CNN-based approaches achieve accuracy rates exceeding 90%, representing a substantial improvement over manual methods. This finding aligns with the broader trend of AI excellence in image analysis tasks and suggests that automated cephalometric analysis is ready for clinical implementation [28].

Treatment duration prediction, while showing promising results with mean absolute errors of 4.8 months, still faces challenges in achieving the clinical accuracy needed for routine use. The 68-84% accuracy within a 3-month window, while better than traditional methods, may not meet the precision requirements for optimal patient counseling and practice management [29].

4.2 Technological Advances and Trends

Research activity peaked between 2020-2022, with performance improvements plateauing in recent years **(Figure 4).** The dominance of deep learning approaches, particularly CNNs, reflects the evolution of AI technology and its superior capability in handling complex, high-dimensional orthodontic data.

Figure 4. Temporal Trends in AI Orthodontics Research 2015-2024



The trend toward ensemble methods and multimodal integration suggests that future developments will focus on combining different AI techniques and data sources to maximize predictive accuracy [30].

The integration of 3D imaging data with traditional 2D radiographs represents a significant advancement, enabling more comprehensive analysis of craniofacial structures and treatment changes. Studies incorporating multimodal data consistently showed 12-18% improvement in performance, indicating that comprehensive data integration is crucial for optimal AI performance [31].

4.3 Clinical Implications

4.3.1 Enhanced Diagnostic Accuracy

AI applications in cephalometric analysis offer the potential to standardize diagnostic procedures and reduce inter-examiner variability. The 91.4% average accuracy in landmark detection, with processing times under 2 seconds, could significantly improve workflow efficiency while maintaining or improving diagnostic quality [32].

4.3.2 Improved Treatment Planning

AI-assisted treatment planning systems showing 82-96% agreement with expert clinicians suggest that these tools can serve as valuable decision support systems. The 35-67% reduction in planning time could have significant implications for practice efficiency and cost-effectiveness [33].

4.3.3 Patient Communication and Consent

More accurate treatment duration prediction (MAE of 4.8 months vs. 7.3 months for traditional methods) enables better patient counseling and informed consent processes. However, the current accuracy levels may still require careful communication about prediction uncertainties [34].

4.4 Limitations and Challenges

4.4.1 Data Quality and Standardization

The review identified significant variability in data quality, imaging protocols, and outcome measures across studies. This heterogeneity limits the ability to directly compare results and develop standardized AI models. The lack of standardized datasets and evaluation metrics represents a major barrier to progress in this field [35].

4.4.2 External Validation and Generalizability

Only 18% of studies included external validation, and the 8.3% average performance decrease in external validation highlights concerns about model generalizability. The predominance of single-center studies (74%) further limits the applicability of findings to diverse clinical settings [36].

4.4.3 Clinical Integration Challenges

Despite promising performance metrics, few studies addressed practical implementation challenges. Issues including computational requirements, integration with existing systems, and clinician training need systematic attention for successful clinical deployment [37].

4.5 Ethical and Regulatory Considerations

The integration of AI in orthodontic practice raises important ethical considerations that were inadequately addressed in most studies. Issues of data privacy, algorithmic bias, clinical responsibility, and patient autonomy require careful consideration as these technologies move toward clinical implementation [38].

Regulatory pathways for AI-based medical devices are evolving, with recent FDA guidance providing frameworks for software as medical devices (SaMD). However, the specific requirements for orthodontic AI applications remain unclear, potentially slowing clinical adoption [39].

4.6 Future Research Directions

4.6.1 Standardization and Validation

Future research should prioritize the development of standardized datasets, evaluation metrics, and validation protocols. Large-scale, multi-center studies with diverse populations are needed to establish the generalizability and clinical utility of AI applications [40].

4.6.2 Interpretable AI

The “black box” nature of many deep learning models limits clinical acceptance and trust. Research into explainable AI techniques that provide insights into model decision-making processes is crucial for clinical adoption [41].

4.6.3 Longitudinal Studies

Most current studies focus on short-term outcomes. Long-term studies examining post-treatment stability, patient satisfaction, and treatment success over extended periods are needed to fully validate AI applications [42].

4.6.4 Integration with Digital Workflows

Future research should explore seamless integration of AI tools with existing digital orthodontic workflows, including practice management systems, imaging software, and treatment planning platforms [43].

4.7 Comparison with Previous Reviews

This review builds upon previous systematic reviews in the field while providing more comprehensive coverage of recent developments. Compared to earlier reviews by Johnson et al. (2021) and Smith et al. (2022), our analysis includes nearly twice as many studies and provides more detailed performance metrics [44,45].

The improved performance metrics observed in recent studies (2022-2024) compared to earlier research suggest rapid advancement in the field, with accuracy improvements of 5-12% across different applications. This trend indicates that AI technology in orthodontics is rapidly maturing [46].

4.8 Strengths and Limitations of This Review

4.8.1 Strengths

- Comprehensive search strategy across multiple databases
- Rigorous methodology following PRISMA guidelines
- Large sample of studies (n = 127) with substantial patient population (n = 45,672)
- Detailed analysis of multiple AI applications
- Quality assessment using established tools

4.8.2 Limitations

- Heterogeneity in study designs prevented meta-analysis
- Limited availability of long-term follow-up data
- Language restriction to English publications

4.9 Clinical Recommendations

Based on the evidence reviewed, we propose the following recommendations for clinical practice:

1. Immediate implementation: AI-based cephalometric landmark detection systems are sufficiently mature for clinical use, particularly in high-volume practices.
2. Cautious adoption: Treatment duration prediction tools should be used as adjuncts to clinical judgment rather than standalone decision-making tools.
3. Research participation: Clinicians should consider participating in multi-center validation studies to contribute to evidence development.
4. Continuing education: Investment in AI literacy and training for orthodontic professionals is essential for successful technology adoption.
5. Patient communication: Clear communication about AI tool limitations and uncertainties should be maintained in patient interactions.

V. CONCLUSIONS

This comprehensive systematic review demonstrates that artificial intelligence has significant potential for enhancing orthodontic treatment outcome prediction across multiple clinical applications. AI methods consistently outperform traditional approaches, with improvements of 12-18% in accuracy across different domains. Cephalometric landmark detection has reached clinical maturity with >90% accuracy, while other applications show promise but require further development and validation.

The most significant barriers to widespread clinical implementation include limited external validation, heterogeneous study methodologies, and insufficient attention to practical implementation challenges. Future research should prioritize standardization of datasets and evaluation metrics, development of interpretable AI models, and comprehensive clinical validation studies.

As AI technology continues to evolve rapidly, orthodontic professionals must balance enthusiasm for technological advancement with critical evaluation of evidence quality and clinical utility. The integration of AI into orthodontic practice represents a paradigm shift that requires careful consideration of technical, clinical, ethical, and regulatory factors.

The evidence supports cautious optimism about AI’s role in orthodontics, with the potential to enhance diagnostic accuracy, improve treatment planning efficiency, and provide better patient outcomes. However, successful implementation will require continued research, standardization efforts, and thoughtful integration with existing clinical workflows.

Abbreviations

See Table 3 for abbreviation definitions.

Table 3. List of Abbreviations
AI in Orthodontic Treatment Outcome Prediction

Abbreviation	Full Form
AI	Artificial Intelligence
AJO-DO	American Journal of Orthodontics and Dentofacial Orthopedics
ANN	Artificial Neural Network
AUC	Area Under the Curve
CBCT	Cone Beam Computed Tomography
CI	Confidence Interval
CNN	Convolutional Neural Network
CT	Computed Tomography
DL	Deep Learning
FDA	Food and Drug Administration
IMRaD	Introduction, Methods, Results, and Discussion
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning

Abbreviation	Full Form
MRI	Magnetic Resonance Imaging
NLP	Natural Language Processing
NOS	Newcastle-Ottawa Scale
PICO	Population, Intervention, Comparison, Outcome
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QUADAS-2	Quality Assessment of Diagnostic Accuracy Studies-2
ResNet	Residual Neural Network
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristic
SaMD	Software as Medical Device
SD	Standard Deviation
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

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Corresponding Author: [Author Name]
[Institution]
[Address]
Email: [email@institution.edu]
Phone: [phone number]

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