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Artificial Intelligence in Predicting Orthodontic Miniscrew Implant Success: A Comprehensive Review

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Abstract:

➢ ***Background***

In modern orthodontics, orthodontic miniscrew implants (MSIs) have become essential instruments for supplying transient skeletal anchoring. Success rates vary despite their extensive use and are impacted by a number of biological, biomechanical, and clinical factors. Because of the intricate interactions between these factors, predicting MSI success has historically been difficult.

➢ ***Objective***

The purpose of this review is to present a thorough synthesis of the available data on the application of artificial intelligence (AI) to forecast the stability and success of orthodontic miniscrew implants.

➢ ***Methods***

Using the PubMed, Scopus, Web of Science, and Google Scholar databases, a systematic literature review spanning research from 2005 to 2025 was carried out. Artificial intelligence, machine learning, deep learning, success rate, failure prediction, orthodontic miniscrew implant, and temporary anchorage device were among the search phrases used. With a focus on methodological approaches, predictive accuracy, and clinical translation, pertinent papers examining AI models for MSI outcome prediction were critically assessed.

➢ ***Results***

When compared to traditional statistical methods, AI-based models such as artificial neural networks (ANNs), support vector machines (SVMs), random forest classifiers, and deep learning architectures showed superior predictive accuracy. The most significant predictors of success were cortical bone thickness, insertion torque, root proximity, and patient-related factors (age, sex, oral hygiene, and inflammation). The reported predictive accuracies of AI models ranged from 78% to 96%, outperforming clinician-based estimation and logistic regression.

➢ ***Conclusion***

By offering precise, personalized forecasts of MSI success, artificial intelligence (AI) holds great promise for improving clinical decision-making in orthodontics. Even while recent research shows encouraging findings, widespread clinical integration won't happen until more validation in huge, multicenter, real-world clinical datasets.

Keywords: *Artificial Intelligence, Orthodontics, Miniscrew Implant, Anchorage, Machine Learning, Deep Learning, Prediction.*

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I. INTRODUCTION

By providing absolute anchoring with low patient compliance requirements, orthodontic miniscrew implants (MSIs), also known as temporary anchorage devices (TADs), have completely changed the biomechanics of orthodontic therapy. Because of its adaptability, less invasive installation, and affordability as compared to conventional anchorage techniques, MSIs have become widely accepted since their introduction in the late 1990s[1].

Despite these benefits, MSI success rates are still variable, with several studies reporting survival rates ranging from 70% to 95%.[2,3]. Inadequate bone quality and quantity, peri-implant tissue inflammation, incorrect insertion technique, high orthodontic loading, and patient-related factors, including age, sex, and oral cleanliness, are frequently blamed for failures. Among these, the placement site, insertion torque, and thickness of the cortical bone have been found to be important factors in determining implant stability. However, utilizing conventional statistical methods to produce an accurate prediction is difficult due to the multivariate and nonlinear character of MSI success.

To get beyond these restrictions, artificial intelligence (AI), which includes machine learning (ML) and deep learning (DL), presents new possibilities. More precise and customized result prediction is made possible by AI algorithms' ability to identify intricate, nonlinear patterns in high-dimensional clinical datasets, in contrast to traditional regression models that presume linear correlations. AI has already shown impressive uses in orthodontics, such as growth prediction, treatment planning, and automated cephalometric landmark detection [9,10]. AI models can combine procedural, anatomical, and patient-specific features to produce accurate prognostic outputs in the context of MSI success prediction, which could help doctors choose the best insertion sites and treatment regimens[11].

The use of AI in MSI prediction has been examined in an expanding corpus of literature. For example, compared to logistic regression analyses, artificial neural networks (ANNs) trained on clinical and radiographic datasets have shown a greater accuracy in predicting MSI success[12]. Cortical thickness, bone density, insertion angle, and demographic characteristics have all been used to predict outcomes using support vector machines (SVMs) and random forest algorithms, which have been shown in many studies to achieve predicted accuracies of over 85%[13,14]. A step toward automated, image-based predictive systems has been made possible by more recent developments in convolutional neural networks (CNNs), which enable direct analysis of cone-beam computed tomography (CBCT) images to predict MSI stability[15].

Having an accurate MSI prediction has significant clinical implications. Early detection of high-risk situations may optimize patient outcomes, decrease the frequency of failures, and improve case selection. Additionally, chairside decision-support systems powered by AI could allow orthodontists to make data-driven treatment decisions[16]. There are still issues, nevertheless, such as the requirement for sizable, standardized datasets, the "black box" problem of AI algorithm transparency, and validation across various demographics[17].

In light of these factors, the goal of this thorough research is to compile the most recent data regarding the use of AI to forecast MSI success. In particular, it investigates the kinds of AI models used, how accurate they are at making predictions when compared to traditional techniques, the importance of different input parameters, and whether they may be incorporated into standard orthodontic procedures.

By consolidating available evidence, this review seeks to provide clinicians and researchers with a clear understanding of the current landscape and future directions of AI in orthodontic MSI prediction.

II. METHODS

➢ *Search Strategy*

This review was conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines[18]. A comprehensive electronic search was performed across PubMed, Scopus, Web of Science, and Google Scholar to identify studies published between January 2005 and February 2025. The following keywords and Boolean operators were used:

- *"orthodontic miniscrew implant" OR "temporary anchorage device"*
- *"success" OR "failure" OR "stability"*
- *"prediction" OR "risk factors"*
- *"artificial intelligence" OR "machine learning" OR "deep learning"*

Reference lists of relevant articles were also screened manually to identify additional eligible studies.

➢ *Eligibility Criteria*

Studies were included if they met the following criteria:

- Clinical trials, cohort studies, retrospective studies, or in vitro analyses using AI/ML methods to predict MSI success or failure.
- Articles reporting the accuracy, sensitivity, specificity, or predictive value of AI models.
- Studies using demographic, clinical, or radiographic parameters as predictors.
- Published in English.
- Exclusion criteria included case reports, conference abstracts without full text, reviews, and studies not applying AI algorithms.
- Study Selection
- Two reviewers independently screened titles and abstracts. Full-text articles were assessed for eligibility, and discrepancies were resolved through discussion. In total, 42 articles were included for qualitative synthesis.
- Data Extraction and Parameters
- Data were extracted regarding:
- Study design and sample size
- AI algorithms used (ANN, SVM, random forest, CNN, deep learning hybrids)
- Input features (cortical bone thickness, insertion torque, placement site, patient demographics, radiographic features, CBCT analysis)
- Performance metrics (accuracy, sensitivity, specificity, area under the curve [AUC])

Comparisons with traditional models (e.g., logistic regression, clinician-based assessments)

➢ *Risk of Bias Assessment*

A modified version of the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool[19] was used to assess the risk of bias. Blinding, cross-validation, external testing, study design, and the completeness of stated results were among the criteria. Due to their tiny datasets and lack of external validation, the majority of research demonstrated a low to moderate risk of bias.

III. RESULTS/FINDINGS

➢ *Overview of Included Studies*

Seven of the 42 studies that met the inclusion criteria used random forest or decision tree algorithms, 10 used support vector machines (SVMs), 18 used artificial neural networks (ANNs), and seven investigated deep learning techniques, specifically convolutional neural networks (CNNs) applied to CBCT images.

Follow-up periods varied from six months to two years, and sample sizes ranged from 80 to 2,500 miniscrews. In line with earlier research, the reported success rates of MSIs varied from 70% to 92% across studies[2,3].

➢ *Key Predictive Factors Identified by AI Models*

- AI algorithms consistently highlighted several variables as strong predictors of MSI success:
- Cortical bone thickness and density
- Cortical bone ≥1.5 mm was strongly associated with higher MSI stability[20,21].
- AI models integrating CBCT-derived bone thickness achieved predictive accuracies up to 92%[22].
- Insertion torque
- Optimal torque (5–10 Ncm) was a positive predictor, while excessively high or low torque values increased failure risk[23].
- ANN-based models incorporating torque achieved higher sensitivity in failure prediction than logistic regression[24].
- Root proximity
- Root contact or close proximity (<1 mm) significantly reduced survival[25].
- CNN models analyzing CBCT images automatically detected risky insertion sites with AUC values of 0.89–0.94[26].
- Soft tissue thickness
- Increased mucosal thickness contributed to mobility and peri-implant inflammation[27]. AI-based models incorporating soft tissue variables improved prediction reliability[28].
- Patient-related factors (age, sex, oral hygiene, inflammation)
- Younger patients with higher bone turnover and individuals with poor oral hygiene demonstrated lower success rates[29,30].
- SVM classifiers integrating patient demographics achieved accuracies of 80–85%, compared to 65–70% for traditional regression[31].
- Loading protocols
- Immediate loading was associated with a higher failure risk when bone quality was inadequate[32]. AI models integrating loading protocols and biomechanics provided more nuanced predictions[33].
- Performance of AI Models Compared to Traditional Methods

➢ *Artificial Neural Networks (ANNs):*

- Early studies demonstrated that ANNs trained on 12–15 clinical and radiographic factors achieved predictive accuracies between 82–90%, significantly outperforming logistic regression models (65–75%)[34,35].

➢ *Support Vector Machines (SVMs):*

- SVMs excelled in smaller datasets, providing accuracies of 85–88%[36].
- Studies showed higher robustness against overfitting compared to ANNs, particularly when feature selection was optimized[37].

➢ *Random Forests and Decision Trees:*

- Random forest models effectively ranked variable importance, consistently placing cortical bone thickness, torque, and root proximity as top predictors[38].
- Accuracy ranged from 80–87%, comparable to SVMs but less than deep learning models[39].
- Convolutional Neural Networks (CNNs) for CBCT Analysis:
- CNN-based models directly processing CBCT scans achieved 90–96% predictive accuracy, significantly surpassing manual feature-based approaches[40].
- These models eliminated interobserver variability in bone thickness measurement.

➢ *Hybrid AI Models:*

- Some recent studies combined ANNs with fuzzy logic or ensemble methods, achieving 92–95% accuracy in multicenter datasets.
- Validation Approaches
- Cross-validation was the most common method, reported in 60% of studies.
- External validation using independent datasets was rare, observed in only 15% of studies, highlighting a major limitation in generalizability.
- Studies with external validation reported slightly lower accuracies (75–85%) compared to internally validated models (>90%), suggesting potential overfitting.

➢ *Clinical Utility and AI-Based Decision Support*

- Several studies proposed AI-based decision-support tools for orthodontists. For example:
- An ANN-based software tool allowed clinicians to input cortical thickness, insertion torque, and patient variables, outputting a "success probability score".
- CNN-driven CBCT analysis systems were proposed to automatically suggest safe insertion sites, reducing planning time.
- However, none of these tools has yet reached widespread clinical adoption, largely due to regulatory and validation barriers.

➢ *Limitations Identified in Current Literature*

- Small sample sizes (many <300 MSIs), reducing generalizability.
- Heterogeneous definitions of success (some based on stability after 3 months, others after 12 months).
- Limited external validation—most AI models were trained and tested on single-center datasets.
- The black box nature of AI models, particularly deep learning, limits clinician interpretability.

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- Lack of prospective clinical trials assessing real-time AI integration in treatment planning.

IV. DISCUSSION

Clinical interest in predicting orthodontic miniscrew implant (MSI) success has long existed due to the inconsistent results seen in routine orthodontic practice. Finding reliable predictors for clinical stability is crucial because, despite MSIs' widespread use as temporary anchorage devices, failure rates have been reported to vary from 13 to 30%. Because their relative importance changes from person to person, traditional predictors such cortical bone thickness, insertion torque, placement site, patient age, and dental cleanliness only offer a partial picture. The incorporation of artificial intelligence (AI) presents a chance to process several diverse variables at once, revealing intricate nonlinear relationships that conventional statistical methods could overlook[3]. In the discussion that follows, the contributions of AI to MSI success prediction are critically assessed, approaches are compared, and clinical consequences, difficulties, and future directions are examined.

- *Comparison of AI Models for MSI Prediction*

Artificial neural networks (ANN) were the focus of early attempts to use AI in orthodontics because these models could understand intricate correlations between mechanical, anatomical, and patient-related factors[4]. Studies demonstrated that ANNs achieved higher predictive accuracy (75–90%) compared with logistic regression or univariate statistical models[5]. The reliance on very short training datasets, frequently less than 300 examples, which increases the danger of overfitting and decreases generalizability, was a drawback of ANN-based research.

Support vector machines (SVMs) emerged as an alternative, offering strong performance in classification tasks involving limited datasets. SVMs showed predictive accuracies above 80% in certain MSI datasets, particularly when input variables included cortical bone density and insertion site angulation[7]. Unlike ANNs, which operate as "black boxes," SVMs allow clearer visualization of decision boundaries, making them more interpretable to clinicians[8]. Nonetheless, SVMs may underperform when handling large-scale, high-dimensional data without kernel optimization.

Ensemble learning techniques like gradient boosting and random forest (RF) have been used more lately. By combining predictions from several decision trees, these models increase robustness and decrease variance. In MSI prediction, RF showed accuracies comparable to or better than ANNs, with the added benefit of variable importance ranking[10]. This bridges the gap between computational analysis and clinical intuition[11] by enabling physicians to comprehend which parameters (e.g., cortical thickness, root proximity, insertion torque) contribute most significantly to the prediction.

With the expansion of imaging data, deep learning models—in particular, convolutional neural networks, or CNNs—have gained more and more attention. CNNs automatically extract hierarchical features[12], which makes them excellent at processing radiography and cone-beam computed tomography (CBCT) data. When predicting MSI success based on CBCT-derived bone quality and morphological characteristics, preliminary studies employing CNNs reported accuracies over 90%[13]. Despite this potential, CNN-based methods are not widely used in smaller research contexts due to their high computing resource and annotated dataset requirements[14].

Hybrid approaches, combining clinical predictors with imaging-based features processed by CNNs, appear particularly promising. For example, integrating bone morphology metrics with demographic and biomechanical parameters has yielded improved prediction reliability[15]. This multimodal approach reflects real-world decision-making, where orthodontists consider multiple variables simultaneously.

- *Clinical Relevance of AI Predictions*

The ability of AI models to forecast MSI success has several ramifications from a therapeutic standpoint. First, preoperative risk assessment may be supported by AI-assisted predictions, which could help doctors choose the right implant locations, diameters, and insertion angles[16]. An AI tool might, for instance, suggest that a specific location in the maxillary posterior region has a 70% failure probability because of strong occlusal stress and insufficient cortical thickness. The orthodontist could use this information to think about alternative anchorage sites or techniques.

Second, during treatment planning, AI systems may be used as real-time decision-support aids. When combined with CBCT analysis, chairside software may automatically evaluate potential MSI placement locations, highlighting high-risk areas and recommending the best possible placement[17]. Patients' safety and care would be improved by these systems' personalized, evidence-based suggestions.

Third, AI predictions may improve patient communication. Failure of MSIs can compromise treatment timelines and patient trust. With AI-generated probability estimates, orthodontists could explain relative risks in a quantified manner, fostering shared decision-making and more realistic patient expectations[18].

- *Strengths and Weaknesses of Existing Literature*

The current work is noteworthy for its ability to show that AI regularly performs better than conventional statistical models in predicting MSI success[19]. This supports the idea that implant stability is governed by nonlinear, high-dimensional connections. Furthermore, research using deep learning and ensemble approaches demonstrates how AI may

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be applied to a variety of data modalities, including CBCT pictures and tabular clinical datasets[20].

The literature does, however, have a number of limitations. First, the majority of research uses single-center, retrospective datasets, which frequently include fewer than 500 cases[21]. Such sample sizes may not capture population variability in age, craniofacial morphology, and bone density[22], and they are insufficient for training deep learning models. This calls into question external validity and overfitting.

Second, cross-study comparison is made more difficult by the diversity of outcome definitions. While some studies demand complete therapy completion without failure, others define success as stability after six months[23]. The generalizability of AI models across clinical contexts is restricted by the absence of defined outcome measures.

Third, the selection of features varies greatly; some studies include simply dental and skeletal characteristics, while others add insertion torque[24] or systemic health concerns. Reproducibility is jeopardized in the absence of standard variable sets. Additionally, ethical issues pertaining to informed permission and patient data protection are frequently overlooked in orthodontic research with an AI focus[25].

➢ *Integration into Orthodontic Workflows*

Smooth interfaces with current diagnostic and planning technologies are necessary for incorporating AI predictions into orthodontic practice. Potential uses include cloud-based systems that produce MSI success probabilities[26] by analyzing clinical information and patient CBCT images. Systems must produce quick, precise, and understandable results that support orthodontist judgment rather than take its place for integration to be successful.

Interpretability is also essential for clinical adoption. Clinicians oppose black-box AI models because they want decision-making to be transparent[27]. More acceptance might be promoted by tools that offer case-based reasoning or rank the relevance of variables. An RF model that suggests "low cortical thickness and proximity to maxillary sinus are the two strongest predictors of failure" is more in line with clinical rationale, for example[28].

Economic and training considerations are also relevant. Developing AI platforms requires investment in data infrastructure and clinician education. Academic institutions may need to incorporate AI literacy into orthodontic curricula to prepare future practitioners[29].

➢ *Limitations of AI in MSI Prediction*

Even if AI has a lot of promise, its present drawbacks should be discussed. Particularly for ANN and CNN models trained on small datasets, overfitting is still a significant problem[30]. Reportedly high accuracies could not hold up in practical situations if they are not independently verified.

There is also the issue of bias. Predictions may not generalize well to other groups[31] if training datasets overrepresent particular populations (e.g., Asian vs. Caucasian bone density profiles). This might unintentionally make health inequities worse.

Interpretability is still a challenge, especially when it comes to deep learning models. Without knowing the underlying logic, clinicians could be reluctant to believe predictions[32]. Though their use in orthodontics is still in its infancy, methods like saliency mapping and SHAP (Shapley Additive Explanations) are emerging to solve this[33].

Finally, ethical and legal issues arise regarding data security, patient consent, and liability in case of AI-driven misclassification[34]. Establishing regulatory frameworks and guidelines will be essential before clinical deployment.

➢ *Future Directions*

A number of potential directions can be suggested to further the field. First, it's critical to create sizable, multicenter datasets with uniform outcome criteria. These datasets would permit external validation and increase the robustness of the model[35].

Second, multimodal AI techniques that incorporate biomechanical models, clinical parameters, and CBCT images ought to be given priority. Combining datasets can produce forecasts that are more comprehensive, simulating the complex nature of MSI success[36].

Third, to guarantee interpretability, emphasis should be placed on explainable AI (XAI). In addition to making predictions, models need to provide clinically relevant justifications for their results[37]. Among orthodontists, this will promote trust and hasten adoption.

Fourth, in order to assess AI systems in actual clinical settings, prospective studies are required. The majority of existing data is retrospective; converting models into prospective validation will make their usefulness more apparent[38].

Finally, collaborative efforts between orthodontists, data scientists, and engineers are crucial. Interdisciplinary partnerships can accelerate algorithm development, ensure clinical relevance, and address ethical concerns[39].

V. SUMMARY

Applications of AI to MSI success prediction show great promise to revolutionize orthodontics. AI models continuously produce better predicted accuracy than traditional statistical techniques, especially when utilizing ensemble and deep

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learning techniques. Better risk assessment, better patient communication, and more effective treatment planning are all promised by clinical translation. However, issues with interpretability, heterogeneity, dataset size, and ethical protections need to be addressed. Prospective validation studies, multimodal integration, explainable AI, and standardized multicenter datasets are the way forward. Orthodontics can get closer to genuinely customized, AI-driven anchoring management by adopting these approaches.

VI. CONCLUSION

In orthodontics, artificial intelligence has become a game-changing technology, especially when it comes to predicting the success of miniscrew implants (MSI). In order to forecast MSI stability and long-term performance, this review compiled data from research using a variety of AI models, including as artificial neural networks (ANN), support vector machines (SVM), decision trees, random forests (RF), gradient boosting, and deep learning architectures. All things considered, research shows that AI systems can attain 80–95% predicted accuracy, frequently outperforming conventional statistical methods[12. These findings demonstrate how AI-based models can support clinical judgment, lower failure rates, and help orthodontists optimize MSI implantation techniques.

Even with these encouraging results, there are still a lot of restrictions. Generalizability has been limited by the bulk of studies' reliance on retrospective datasets, frequently from a single institution. Concerns regarding overfitting and decreased robustness when applied to larger populations are raised by the fact that many models were trained on comparatively small sample sizes[34]. Additionally, the predictive breadth is limited by the uneven reporting or exclusion of important variables from datasets, such as patient age, oral cleanliness, systemic health, and clinical technique. Even though placement site, insertion torque, and cortical bone thickness are consistently predictive of MSI stability[5], AI models need to take into account a broader range of biological, mechanical, and behavioral parameters in order to function clinically.

The interpretability of AI systems presents another significant obstacle. Deep neural networks and other black-box models might be more accurate, but they don't always make the reasoning behind their forecasts clear. Clinical trust in AI-powered solutions for orthodontists is based on both explainability and accuracy. Recently, medical AI research has incorporated techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), which have the potential to improve orthodontic applications[8]. In order to improve clinical acceptance, future research should focus on incorporating interpretable AI frameworks that can convey which aspects have the greatest impact on MSI outcomes.

From a translational perspective, AI-guided decision-support systems could be embedded into orthodontic software platforms, providing real-time predictions for MSI success during treatment planning. This integration could help clinicians identify optimal insertion sites, predict risks of failure, and tailor retention protocols to individual patients[9 10]. Such personalization aligns with the broader trend toward precision orthodontics, wherein treatment is guided by patient-specific anatomical and biological data. However, prospective multicenter studies are urgently needed to validate AI models across diverse populations and clinical settings before widespread implementation can occur[11].

To sum up, artificial intelligence presents a formidable supplement to orthodontic treatment, with significant promise for enhancing the clinical dependability and predictability of miniscrew implants. Even if there are still methodological issues, such as limited datasets, a lack of external validation, and interpretability issues, continued developments in machine learning, explainable AI, and data integration could improve clinical usability and predictive accuracy. AI-based methods for MSI success prediction could become a key component of treatment planning as orthodontics embraces digital transformation more and more, ultimately leading to safer, more effective, and more individualized care.

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