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AI-driven prediction of dental implant numbers to be placed for patient-specific treatment planning



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ABSTRACT

Introduction and aims: The growing prevalence of edentulism, particularly in aging populations, has increased the demand for accurate and consistent dental implant treatment planning. Determining the number of implants required in edentulous areas is a complex process influenced by various clinical and anatomical factors. Traditional approaches rely heavily on clinician experience and image interpretation, often resulting in variability. This study aimed to develop and evaluate a deep learning-based regression model, using panoramic radiographs and clinical data, to predict the optimal number of implants required for edentulous patients and to support standardised, data-driven treatment planning.

Methods: This retrospective study included 628 patients (341 females, 287 males; mean age 60.0 ± 14.7 years) treated with dental implants at Daejeon Dental Hospital, Wonkwang University between 2019 and 2023. A total of 919 edentulous regions of interest (ROIs) were labeled with the number of implants determined by consensus between 2 oral and maxillofacial surgeons using panoramic and CBCT imaging. Preprocessing involved ROI extraction, zero-padding, resizing, normalisation, and channel duplication. A Vision Transformer (ViT)-based regression model was constructed and trained using transfer learning from the pre-trained ViT-Base (google/vit-base-patch16-224-in21k) model. The [CLS] token output was passed through a custom regression head to predict implant counts. Model training employed 5-fold cross-validation with the Adam optimiser, Mean Squared Error (MSE) loss function, and dropout for regularisation. Performance was evaluated using MSE, mean absolute error (MAE), R^2 , and explained variance score (EVS), complemented by visual diagnostic plots.

Results: The ViT-based model achieved strong predictive performance with an MSE of 0.0460, MAE of 0.0871, and both R^2 and EVS values of 0.9189. Visual diagnostics (residual, box, and Q-Q plots) confirmed that the model's errors were symmetrically distributed and approximately normal, indicating good model fit and reliability. The model effectively captured spatial relationships within the edentulous areas and demonstrated potential as a quantitative decision-support tool for implant planning.

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Conclusion: This study demonstrated the feasibility of using a deep learning-based ViT regression model to predict the number of dental implants needed in edentulous patients. The model showed high accuracy and explanatory power, suggesting its potential utility in standardising implant treatment planning. However, the study's generalisability is limited by its single-center design and sample size. Future work should incorporate multi-institutional data, 3D segmentation, and additional clinical variables to further improve model accuracy and clinical applicability.

Clinical Relevance: The proposed AI model provides a reliable, data-driven approach to assist clinicians—especially those with less experience—in determining implant quantity for edentulous patients. Our model the potential to enhance consistency in treatment planning, reduce variability and ultimately improve patient care in implant dentistry.

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Introduction

The increasing prevalence of edentulism, particularly in aging populations, has led to a growing demand for dental implant solutions. Implant placement planning is a complex process influenced by multiple factors including anatomical considerations, bone quality, patient-specific characteristics, and clinician experience. Traditionally, implant placement decisions rely on clinical expertise and image interpretation, leading to variability in treatment planning outcomes.

Typically, if the number of missing teeth is 1 or 2, then the same number of implants is placed. However, if the edentulous area is extended, factors such as the occlusal force and length of the alveolar bone must be considered. For instance, in full-arch restorations, techniques like the All-on-4 concept utilise 4 strategically placed implants to support a full fixed bridge, taking into account bone density and anatomical structures.¹ Additionally, if tooth loss occurs in the anterior region, the aesthetic form of the final prosthesis can influence the number and positioning of implants to achieve optimal aesthetic outcomes.² Since the anatomical shape and quality of the alveolar bone vary among individuals, predicting the number of implants to be placed is a crucial factor in developing a treatment plan. Accordingly, dentists use various imaging data to assess the number of implants that can be placed in the missing areas. In particular, panoramic and cone-beam computed tomography (CBCT) imaging are widely used as essential tools for analysing the anatomical structure of the alveolar bone.

In the field of clinical dentistry, the application of artificial intelligence (AI) and deep learning has evolved from early computational models to advanced systems that support clinical data interpretation and decision-making. The integration of these technologies has contributed to improved diagnostic accuracy, optimised treatment planning, and enhanced prognostic predictions across various dental specialties, including periodontics, conservative dentistry, oral medicine, pathology, prosthodontics, pediatric dentistry, forensic odontology, oral and maxillofacial surgery, orthodontics, and orofacial pain management.³ Despite the growing integration of AI in dentistry, several challenges and ethical considerations remain. Key obstacles include limited data availability, algorithmic bias, and uncertainties regarding human accountability. To address these issues, strategic

approaches such as promoting AI literacy among dental professionals, establishing clear regulatory frameworks, and implementing targeted AI applications have been proposed. Furthermore, ethical concerns—particularly those related to patient privacy and transparency in algorithmic decision-making—necessitate ongoing evaluation and the development of robust governance standards to ensure responsible and effective deployment of AI technologies in dental practice.⁴

Yoo et al.⁵ demonstrated the use of deep learning to predict the extraction difficulty for mandibular third molars, a procedure often fraught with variability owing to anatomical complexity. Similarly, deep learning models have been applied to predict paresthesia following third molar extraction, providing valuable insights into postoperative complications.⁶ Additionally, Mun et al.⁷ explored the use of panoramic radiography to predict indications for fractured tooth extraction, highlighting the expanding role of deep learning in detecting dental issues that are otherwise challenging to assess. Deep learning models are widely used in implant surgery. The prediction of osseointegration for dental implants has also benefited from the application of deep learning, as demonstrated by Oh et al.⁸ Their study utilised plain radiographs to forecast the success of dental implants. This is a key challenge in implantology, where success depends on numerous factors, including bone quality and surgical approach. Mun et al.⁹ demonstrated that deep learning models can effectively predict the possibility of immediate implant placement after tooth extraction, supporting the use of panoramic radiography in clinical decision-making for such procedures. Furthermore, Jeong et al. highlighted that cephalometric radiography can assess craniospinal differences and skeletal classification, emphasising AI's growing potential in dental and orthodontic care.¹⁰ The role of deep learning in predicting the necessity for such surgeries, particularly for skeletal malocclusion, has been explored by Shin et al.,¹¹ demonstrating its capacity to support complex decision-making processes in orthodontics. Moreover, deep learning has shown promise in identifying soft tissue profiles that require orthognathic surgery, a critical aspect of orthodontic and surgical treatment planning.¹² Similarly, the application of deep learning models for predicting the postoperative outcomes of orthognathic surgery, as seen in Jeong et al.,¹³ highlights the growing ability of AI models to forecast surgical

results. In addition to these studies, the use of deep learning models to predict the difficulty of impacted mandibular third molar extraction was further expanded by Trachoo et al.,¹⁴ demonstrating the utility of the model in predicting the removal difficulty, which is an essential consideration for improving surgical planning and patient care.

Despite growing interest in deep learning model applications, limited research has focused on predictive modeling to determine the number of implants required in edentulous patients. The ability to predict implant placement accurately can aid clinicians in preoperative planning, improve treatment outcomes, and reduce procedural inconsistencies. This study aimed to address this gap by developing and evaluating a deep learning-based regression model to predict the optimal number of implants for edentulous patients. Specifically, the study will train a regression model to predict the number of implants evaluated by dentists based on panoramic images and validate the performance of the model. By comparing their predictive performances, this study sought to identify the most effective model for supporting clinical decision-making in implant dentistry.

Methods

Research subjects and data construction

This study was conducted on 628 patients who visited Daejeon Dental Hospital, Wonkwang University for dental implant treatment between January 2019 and December 2023. The inclusion criteria for the data were as follows: (1) patients with one or more missing teeth and (2) patients with images of sufficient quality for diagnosis. Based on these criteria, a total of 628 patients were ultimately included in the study.

The data included a sex- and age-diverse patient population comprising 341 females (54.3%) and 287 males (45.7%). The mean age of the patients was 60.0 ± 14.7 years, ranging from 19 to 92 years. More specifically, the mean age of women was 61.6 ± 14.2 years (19-88 years), and the mean age of men was 58.0 ± 15.1 years (19-92 years).

Panoramic radiographs were obtained for all 628 patients using a PCH-2500 (Vatech, Hwaseong, Republic of Korea; current, 10 mA; voltage, 72 kV; exposure time, 13.5 s) or Promax (Planmeca, Helsinki, Finland; current, 12 mA; voltage, 72 kV; exposure time, 15.8 s) instrument. Data from the panoramic radiographs consisted of a 12-bit Digital Imaging and Communications in Medicine file with heights ranging from 1316 to 1504 and widths ranging from 2570 to 2872. In addition, CBCT was performed to confirm 3-dimensional anatomical conditions in all cases.

The main objective of this study was to develop a regression model that predicts the number of teeth that can be implanted based on patient data. To construct the training dataset, we defined consecutive edentulous areas within the images as the Region of Interest (ROI). Each ROI was labeled with the number of possible implants that could be placed (Implant Count, IC). For instance, in a case where 3 teeth were missing from the maxillary left first premolar (#14) to the first molar (#16), the bounding box for this area was annotated with the corresponding number of possible implants (eg, 3) (Figure 1). Two oral and maxillofacial surgeons cross-evaluated and determined the feasibility and number of implants to be placed using oral and radiological examinations based on panoramic and CBCT images. When the number of implants determined by the 2 oral and maxillofacial surgeons differed, a consensus was reached through discussion. The Public Institutional Review Board (IRB) of South Korea approved this study (P01-202411-01-029). Due to the

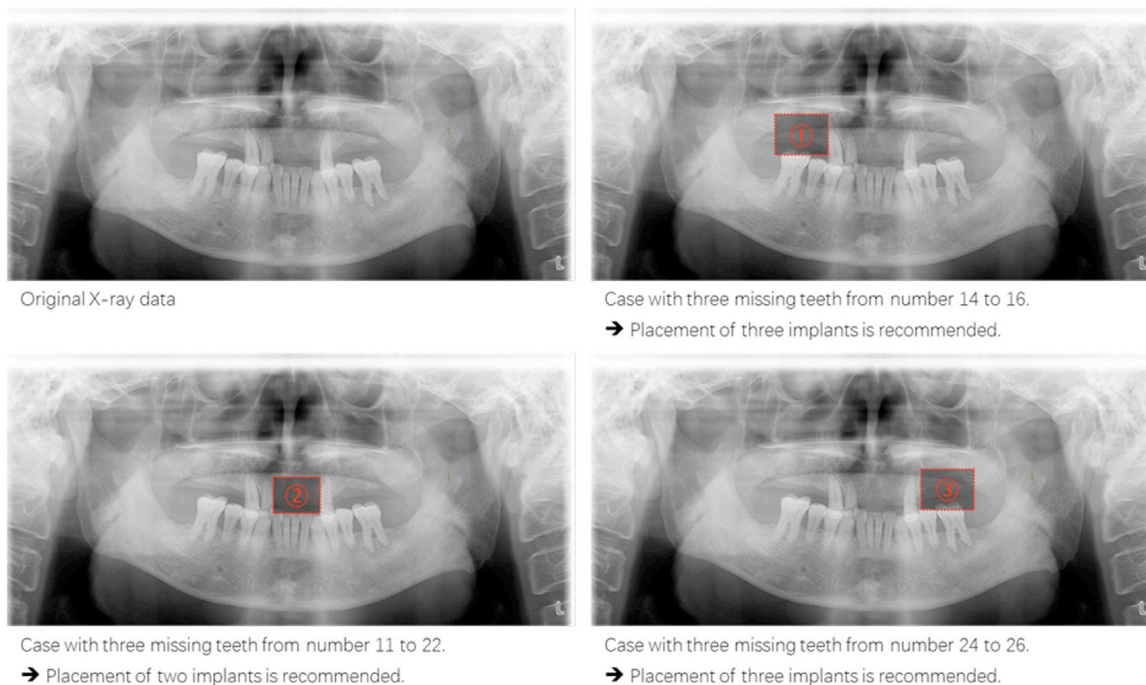


Fig. 1 – Clinical examples for data collection.

absence of personal identification data, the IRB waived the need for written or verbal informed consent from the subjects. Through this process, a total of 919 data points, each comprising an edentulous ROI and its associated IC, were acquired from the 628 patients (Table 1).

Data preprocessing

The dental panoramic radiographic images used as training data for the AI model in this study underwent a multi-stage systematic preprocessing procedure to optimise prediction performance. First, to prevent the model from being distracted by anatomical structures unrelated to the analysis—such as the mandibular canal or maxillary sinus—regions of interest (ROIs) were precisely cropped around the pre-identified areas of continuous tooth loss. This step was designed to eliminate unnecessary noise and guide the model's attention toward the actual regions of analytical relevance. Second, to address the imbalance in image size and aspect ratio caused by the cropping process, a zero-padding technique was applied. Specifically, based on the longer axis of each image, padding with pixel values of zero was added to both ends of the shorter axis, standardising all images into a square format with a 1:1 aspect ratio. This allowed for a consistent input format without distorting anatomical structures. Third, the square images were resized to 224×224 pixels to meet the model's input requirements, and pixel value normalisation was performed to improve training stability and convergence speed. Furthermore, considering that the input format of the pre-trained Vision Transformer (ViT) model requires 3 channels (RGB), the single-channel grayscale images were duplicated across all 3 channels to form identical 3-channel inputs.¹⁵

Model implementation

In this study, to address the regression task of predicting the required number of dental implants based on panoramic

radiographic images, we selected and designed a model architecture capable of effectively capturing both local image features and global relationships across tooth loss regions. This task goes beyond simple pattern recognition, requiring comprehensive consideration of factors such as the size and location of missing teeth and their relationships with surrounding anatomical structures. To meet these demands, we adopted the ViT architecture as the core model, given its strong capability in understanding the overall context of images. Unlike conventional CNN-based models with limited local receptive fields, ViT overcomes such constraints by leveraging an attention mechanism that effectively models long-range dependencies.^{16–19} This aligns well with the core problem of this study, where structural relationships between teeth and the spatial context of edentulous areas are crucial for implant necessity prediction.

To maximise training efficiency and prediction performance, we employed a transfer learning strategy. Specifically, we utilised the Google/vit-base-patch16-224-in21k model, which had been pre-trained on ImageNet-21k, a large-scale dataset consisting of approximately 14 million images.²⁰ The ViT-Base model is composed of 12 Transformer encoder layers, allowing for deep representation learning. Input images were resized to 224×224 pixels and divided into non-overlapping 16×16 patches. These sequences of patches are processed similarly to word sequences in natural language processing, enabling effective modeling of spatial information within the image. Considering that the pre-trained model expects 3-channel (RGB) inputs, we duplicated the grayscale panoramic images into 3 identical channels during preprocessing to match the required input format. The ViT backbone generates high-dimensional feature vectors from these preprocessed inputs, among which the final output of the (CLS) token is regarded as a summary representation of the entire image and is used as the representative input for regression prediction. Since the (CLS) token interacts with all patches via attention mechanisms, it encapsulates the global image information, making it well-suited for continuous variable prediction.

The 768-dimensional feature vector of the (CLS) token, extracted by the ViT backbone, is fed into a custom-designed regression head tailored for predicting the number of required implants. This regression module is structured to enhance prediction accuracy while preventing overfitting. The first fully connected layer reduces the 768-dimensional input to 256 dimensions, improving computational efficiency and refining the feature space. A ReLU activation function is used to introduce non-linearity, enabling the model to learn the complex relationships between image features and implant requirements. To further improve generalisation and reduce dependency on specific features, a dropout layer with a 30% drop rate is included during training. Finally, the output layer transforms the 256-dimensional vector into a single scalar value, representing the predicted number of required dental implants—a continuous variable. Through this architectural design, the model is optimised to achieve high predictive performance by combining the powerful feature representation capabilities of the pre-trained ViT with a purpose-built regression analysis module (Figure 2).

Table 1 – Patient characteristics and data details.

	Count	Ratio
Patient	628	-
Data	919	-
Gender		
Female	341	54.30
Male	287	45.70
Age		
10-20	13	2.07
20-30	23	3.66
30-40	23	3.6
40-50	66	10.51
50-60	136	21.66
60-70	212	33.76
70-80	116	18.47
Over 80	39	6.21
Classes		
1	531	57.78
2	287	31.23
3	78	8.49
4	23	2.50

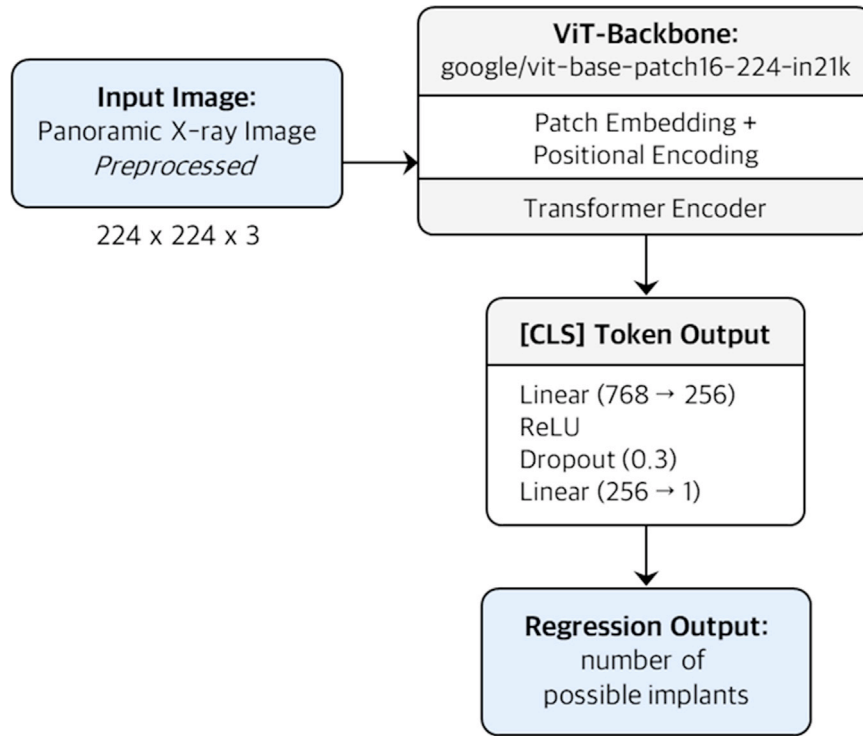


Fig. 2 – Schematic diagram of model input data and feature extraction.

Model training procedure

In this study, a sophisticated strategy encompassing data partitioning, hyperparameter optimisation, loss function selection, and stable optimisation techniques was employed to effectively train the deep learning-based regression model. To ensure robust evaluation and minimise overfitting, a 5-fold cross-validation scheme was implemented, wherein the dataset was partitioned into 5 equally sized subsets. For each fold, the model was trained on 4 subsets and validated on the remaining one, with the process repeated 5 times to cover all partitions. The final performance was reported as the average of the validation results across all folds.

Prior to training, an extensive exploration of various hyperparameter combinations was conducted. As a result, a learning rate of $1e-4$, batch size of 32, and dropout rate of 0.3 were found to yield the best performance. For the loss function, mean squared error (MSE) was adopted, as it is well-suited for regression tasks. The Adam optimiser was chosen for its computational efficiency and stable convergence properties.²¹ Training was conducted for up to 1000 epochs, with continuous monitoring of the validation loss. The model state corresponding to the lowest validation loss was automatically saved and later used for final testing.

Evaluation of the performance

Various metrics are used to evaluate the performance of the trained regression model.²²⁻²⁶ The MSE, calculated as the average of the squared differences between the

predicted and actual values, was used to numerically represent the magnitude of the prediction errors. This metric is particularly useful for precisely assessing model performance because larger errors contribute disproportionately to the value. The mean absolute error (MAE), which computes the average of the absolute differences between the predicted and actual values, was used as an intuitive indicator to understand the magnitude of the prediction errors. Additionally, the R^2 score was employed to evaluate how well the model explained the data, with values closer to 1 indicating higher explanatory power. Finally, the explained variance score (EVS) was used to measure how well the model predictions accounted for the variability in the actual data. Higher values (closer to 1) signify better model performance.

In addition to these numerical metrics, linear regression analysis was conducted to assess the linear relationship between the predicted and actual values. Furthermore, several diagnostic plots were employed to visually inspect the assumptions and residual behavior.²⁷⁻²⁹ A residual plot was generated to examine whether the residuals were randomly distributed, which indicated a good model fit without systematic errors. The box plot of the residuals helped identify outliers and assess the symmetry and spread of the prediction errors. Finally, a quantile-quantile (Q-Q) plot of the residuals was used to evaluate the normality assumption of the residuals by comparing their distribution to a theoretical normal distribution. These visual assessments complemented the numerical metrics and provided a comprehensive understanding of model validity and robustness.

Results

In this study, the performance of the proposed Vision Transformer-based regression model was comprehensively evaluated using both quantitative metrics and visual analysis. To numerically assess the model's prediction accuracy, 4 representative regression evaluation metrics—MSE, MAE, R^2 score, and EVS—were employed. The experimental results yielded an MSE of 0.0460 and an MAE of 0.0871, indicating that the predicted number of implants was highly consistent with the actual values. Notably, the MAE being less than 0.1 implies that most of the predicted values deviate from the ground truth by no more than ± 1 implant, suggesting potential for clinical applicability.

Additionally, the R^2 and EVS values, both calculated to be 0.9189, reflect the model's strong explanatory power and generalisation ability. These values indicate that the model successfully accounts for approximately 91.9% of the variability in the dataset, demonstrating effective learning of critical patterns and structures from the input images. Given that an R^2 score closer to 1 denotes higher explanatory power, the model trained in this study can be considered to exhibit excellent regression performance (Table 2).

Beyond quantitative evaluation, further analyses were conducted to visually diagnose the reliability of the predictions and validate model assumptions. A linear regression analysis between predicted and actual values revealed a strong positive correlation, with data points densely clustered around the $y = x$ line, indicating that the model preserves the overall scale and distribution of the target variable (Figure 3A). The residual plot showed that residuals were randomly distributed across the range of predicted values, suggesting homoscedasticity and independence of errors (Figure 3B). The box plot further visualised the central tendency and dispersion of residuals, showing that most residuals fell within the IQR and that the number of outliers was limited (Figure 3C). Finally, a quantile-quantile (Q-Q) plot analysis was conducted to evaluate the normality assumption of residuals (Figure 3D). The residual distribution is closely aligned with the theoretical normal distribution, indicating that the regression model satisfies traditional regression assumptions well, thereby supporting its reliability and interpretability.

In conclusion, the proposed Vision Transformer-based regression model demonstrated excellent performance across both quantitative metrics and visual diagnostics. The model achieved sufficient accuracy and reliability to be applicable to the real-world task of predicting the required number of dental implants from panoramic radiographs. These findings suggest its potential as a quantitative decision-support tool in future dental image-based diagnostic systems.

Discussion

With improvements in medical systems, both average and active life expectancies have increased, leading to a higher proportion of elderly patients needing dental implants. However, establishing treatment plans for extensively edentulous areas can be challenging. While there are several theoretical guidelines regarding how many implants should be placed in edentulous areas, the final number of implants to be placed is largely dependent on the dentist's experience. This can lead to significant difficulties for less-experienced dentists and can cause confusion in patients owing to varying treatment plans among different dentists.

Building upon the work of Al-Asali et al.,³⁰ who introduced a deep learning-based approach for 3D bone segmentation and implant site prediction using CBCT images, our study extends the application of AI in implant dentistry by shifting the focus from anatomical localisation to clinical decision-making support. While their work significantly contributes to the automation of bone segmentation and visualisation for surgical planning, our study complements this approach by developing an AI-driven model that predicts the optimal number of implants in edentulous patients. By integrating not only radiographic information but also patient demographic and clinical variables, our model addresses the broader question of treatment planning quantity. In this way, our study aligns with and builds upon previous efforts in AI-driven dental implant planning, offering an additional layer of clinical decision support that can enhance consistency and objectivity in the preoperative phase, especially for less-experienced clinicians.

To the best of our knowledge, this is the first study to predict the number of implants placed in missing areas using a deep learning model. These predictions can assist dentists in formulating treatment plans and offering new options.

The findings of this study suggest that deep learning can be an effective tool for aiding clinical decision-making in dental implant placement. In particular, this study constructed a regression model based on the ViT architecture, which has advanced visual information understanding capabilities. As a result, the model showed excellent predictive performance with a MSE of 0.0460, a MAE of 0.0871, a R^2 of 0.9189, and an EVS of 0.9189. This indicates that the deep learning model effectively learned the visual characteristics and spatial context of the edentulous area, demonstrating its potential to serve as a practical clinical decision-making tool for clinicians with limited experience. In particular, the global attention mechanism based on the Transformer effectively captured relationships between distant image patterns, such as the location and number of tooth defects and surrounding alveolar bone structures, thereby complementing the local receptive field limitations of CNN-based models.

Moreover, this study's reliance on panoramic images as primary data sources highlights the importance of high-quality imaging in predictive modeling. Future research could explore the integration of additional clinical parameters, such as bone density measurements and occlusal force analysis, to further refine model accuracy. Additionally, the inclusion of 3-dimensional segmentation techniques could enhance the model's ability to understand spatial

Table 2 – Performance metrics for the regression model.

	MSE	MAE	R^2 Score	EVS
LR	0.0208	0.0843	0.9622	0.9628

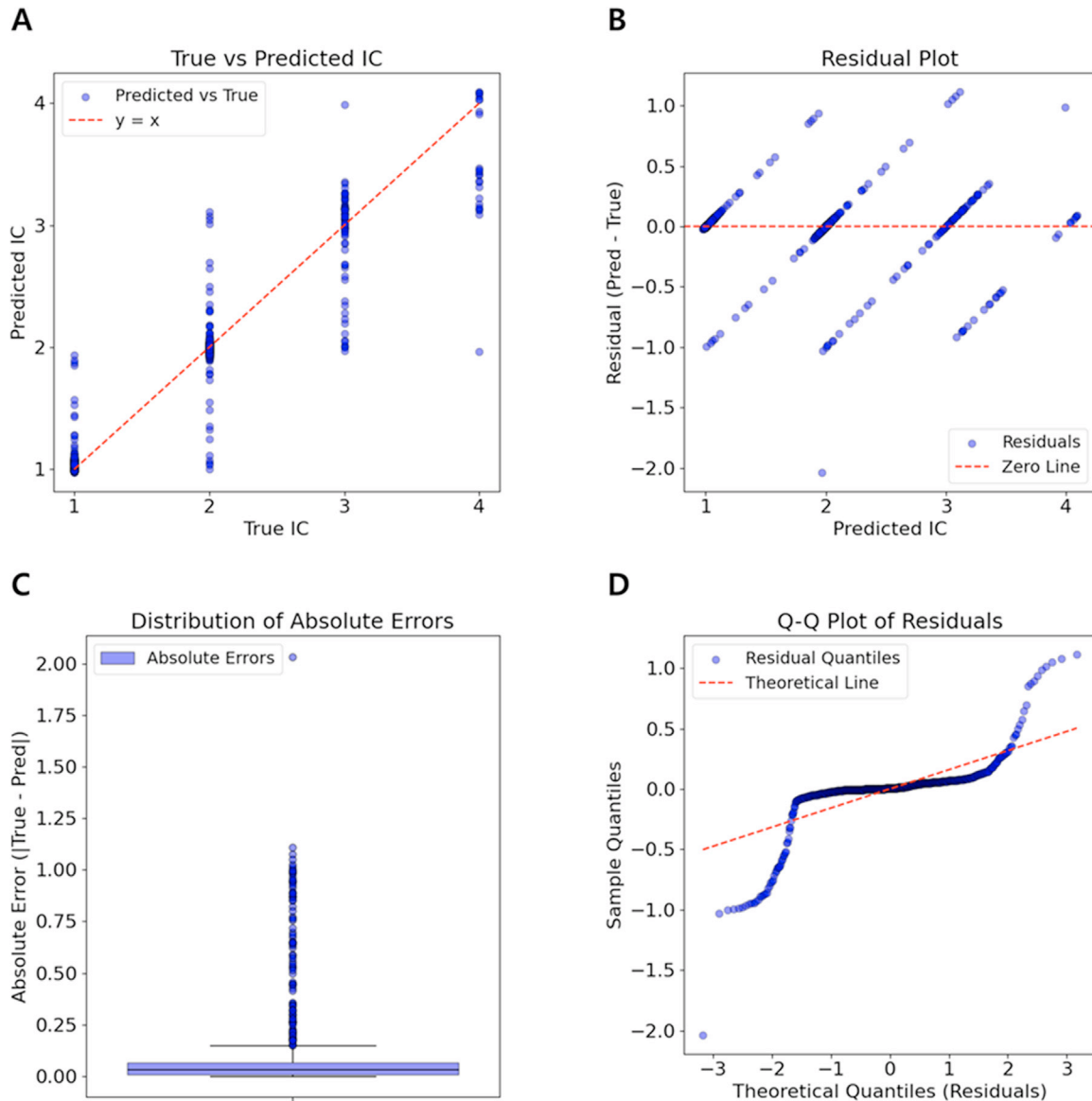


Fig. 3 – Visual Analysis of Prediction-Error Dynamics in Regression Model. (A) Linear regression analysis. (B) Residual plot. (C) Box plot of residuals. (D) Q-Q Plot of Residuals.

relationships in edentulous areas, leading to more precise implant placement predictions.

This study had several limitations. Two experts evaluated the number of implants that could be placed. If a larger number of dentists evaluate the number of implants that can be placed, a more reliable deep learning model can be obtained. Second, this study utilised a relatively small sample size from a single center. To enhance the generalisability of the trained models and their relevance in clinical practice, it is essential to train the models further using data from multiple healthcare institutions. Thus, it is essential to collect and train with additional data representing a variety of environments, equipment, and patient conditions.

Despite these limitations, this study lays the groundwork for future advancements in AI-based dental implant

planning. As deep learning techniques continue to evolve, incorporating real-time decision support systems into clinical workflows can improve treatment consistency and efficiency. Further validation studies are required to confirm the robustness of this model in diverse patient populations and clinical settings. Finally, this study highlights the potential of artificial intelligence in revolutionising personalised dental care and improving patient outcomes.

Conclusion

In this study, we developed an AI-driven model to predict the number of implants in edentulous patients. The results showed that the random forest model had the highest

prediction performance, which was attributed to its ability to effectively learn interactions between complex variables. This study suggests that deep learning can help establish dental implant treatment plans; however, it has limitations in fully reflecting the patient's anatomical characteristics and the clinician's experience. Additional research using multi-institutional data is needed to generalise the study, and prediction accuracy can be further improved by integrating 3-dimensional segmentation technology and additional clinical data in the future. Ultimately, this study suggests the possibility of AI-based dental treatment planning. Further research is required to increase the possibility of its clinical use in the future.

Author contributions

The study was conceived by B. C. K. and K. G. K., who conducted the experiments. S.B.M. conducted the experiments. S. R. Y. and B. C. K. generated the data. All authors analysed and interpreted the data. S.B.M., S.R.Y., B.C.K. and K.G.K. prepared the manuscript. All the authors have read and approved the final version of the manuscript.

Conflict of interest

None disclosed.

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Ethics approval and consent to participate

This study was approved by the public Institutional Review Board (IRB) of South Korea (P01-202411-01-029). Due to the absence of personal identification data, the IRB waived the need for written or verbal informed consent from the subjects.

Availability of data and materials

The data used in this study can be made available, if required, within the regulation boundaries for data protection. They are available from the corresponding author (B.C.K.) on reasonable request.

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Not applicable.

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