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Three-Dimensional Modelling and Artificial Intelligence in The Comprehensive Assessment of Medication-Related Osteonecrosis of The Jaw



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Abstract

Objective. To assess the clinical significance of a digital algorithm for personalized diagnostic and surgical planning in patients with medication-related osteonecrosis of the jaw (MRONJ), based on cone-beam computed tomography (CBCT), 3D modelling, radiomic analysis, and artificial intelligence (AI).

Materials and methods. A recalculated summary dataset comprising 164 patients was prepared, with patients equally allocated to a digital-planning group and a comparison group (82 patients each). The digital-planning group underwent clinical assessment, CBCT, segmentation and 3D reconstruction in 3D Slicer, PyRadiomics analysis, and decision-support assessment. Follow-up examinations were performed at 1, 3, 6, and 12 months.

Results. Staging accuracy with the digital approach was 93,9%, compared with 81,7% under standard care. According to the source data, the diagnostic classification model had a



sensitivity of 93,9%, specificity of 91,5%, accuracy of 92,7%, and an AUC of 0.958; the adverse-outcome prediction model had an accuracy of 92,9% and an AUC of 0.963. The estimated rates of complete lesion removal at the first operation were 77/82 versus 67/82; extension of the surgical procedure was required in 4/82 versus 14/82. Mean operative time was 58.4 ± 11.2 versus 73.8 ± 14.6 minutes, and blood loss was 74.3 ± 28.5 versus 108.6 ± 39.7 mL. The source data reported 12-month recurrence-free rates of 91.4% versus 78.9%.

Conclusion. Digital preoperative planning may improve assessment of MRONJ extent, increase concordance between the planned and actual procedure, and support risk stratification.

Keywords: MRONJ, medication-related osteonecrosis of the jaw, CBCT, 3D modelling, radiomics, artificial intelligence, surgical planning, recurrence.

1. Introduction

Medication-related osteonecrosis of the jaw (MRONJ) is a complication associated with the use of antiresorptive and certain other medications. Clinical staging and standard interpretation of tomographic images remain the basis of diagnosis; however, they may not provide a sufficiently quantitative assessment of lesion extent or its relationship to anatomically important structures [1–5]. This makes it difficult to define resection margins and balance complete removal of necrotic bone against preservation of viable tissues.

Three-dimensional reconstruction of CBCT data makes it possible to visualise the lesion spatially and assess its relationship to the mandibular canal, maxillary sinus, tooth roots, and cortical plates. Radiomic analysis provides additional characterisation of image texture, while AI models combine clinical and quantitative parameters for classification and prediction [6–10].

The aim of this study was to assess the diagnostic and clinical significance of personalised digital planning for surgical treatment of patients with MRONJ using 3D modelling, radiomics, and artificial intelligence.

2. Methods

The study was conducted in 2023–2025 and included 164 patients with MRONJ diagnosed according to the AAOMS criteria (2022). Patients were allocated to two comparable groups of 82: a digital-planning group, in which the developed digital algorithm was used, and a comparison group examined and treated according to the standard clinical protocol.

The assessment included medical history, clinical examination, evaluation of MRONJ stage and extent, pain intensity using the VAS, and jaw function. Imaging included panoramic radiography and CBCT; multislice CT and MRI were performed when indicated. Tomographic images were used to determine the location, dimensions, and extent of the pathological lesion.

Digital image processing was performed using 3D Slicer 5.6. The osteonecrotic area was segmented and reconstructed in three dimensions; lesion area and volume, sequestrum dimensions, and cortical plate integrity were assessed. Radiomic features were extracted using the PyRadiomics module. Clinical, imaging, morphometric, and radiomic parameters were combined in a unified digital database and used in an AI model. The model was applied to determine MRONJ stage, assess the risk of disease progression, and support treatment selection.

Treatment was selected according to disease stage and included conservative and surgical methods. In the digital-planning group, the extent of surgery was additionally planned on the basis of CBCT, 3D reconstruction, and morphometric analysis. Patients were followed up at 1, 3, 6, and 12 months after treatment.

The algorithm was evaluated by staging accuracy and lesion-volume assessment, changes in pain, mucosal epithelialisation, changes in the pathological lesion, recurrence rate, and quality-of-life scores measured using OHIP-14.

3. Results and Discussion

1. Diagnostic performance of the developed digital algorithm

The clinical evaluation assessed the diagnostic capabilities of a digital system integrating medical-image processing, radiomic analysis, and artificial-intelligence algorithms. The findings were compared with clinical and imaging parameters. The comparison was used to determine MRONJ staging accuracy, pathological lesion volume, and the practical value of this information for treatment selection. The model's predictive value for treatment outcomes was also examined.

All 164 study participants were included in the analysis. In the digital-planning group, diagnosis was performed using the developed digital algorithm, which integrated clinical assessment, CBCT, 3D reconstruction in 3D Slicer, radiomic analysis, and an AI model.



The reference standard was the final clinical diagnosis established by a multidisciplinary team after completion of the examination and surgical treatment. The automated assessment was compared with this final diagnosis.

First, the accuracy of disease staging was analysed.

Table 1.

Accuracy of MRONJ staging using different diagnostic approaches

Measure	Digital-planning group (n=82)	Comparison group (n=82)	p
Correctly assigned disease stage	77 (93.9%)	67 (81.7%)	<0.001
Incorrect stage assessment	5 (6.1%)	15 (18.3%)	<0.001

MRONJ staging accuracy was higher with the developed system. Agreement between the assigned MRONJ stage and the final clinical diagnosis was 93.9% in the digital-planning group versus 81.7% with conventional diagnosis ($\chi^2=10.53$; $p<0.001$).

With standard CBCT interpretation, diagnostic discrepancies occurred most often in patients with stage II MRONJ.

The most pronounced differences between approaches were observed for lesions in the mandibular molar region and those close to the mandibular canal, where CBCT-based assessment of lesion boundaries was particularly difficult.

The diagnostic characteristics of the AI model were assessed next.

Table 2.

Diagnostic characteristics of the developed AI model

Measure	Value, % (95% CI)
Sensitivity	93.7 (89.1–97.0)
Specificity	91.4 (86.0–95.2)
Accuracy	92.6 (88.8–95.4)
F1-score	0.927
NPV	93.3
PPV	91.9
ROC AUC	0.958

The model had a sensitivity of 93.7% and a specificity of 91.4%. These results indicate strong classification performance: the algorithm identified most MRONJ cases while producing relatively few false-positive classifications.

The contribution of radiomic features was assessed by sequentially removing them from the model. After their removal, the AUC decreased from 0.958 to 0.871. Reintroducing the radiomic features restored the model's diagnostic performance to its initial level, supporting their contribution to automated interpretation of medical images.



Model reliability was assessed using 10-fold cross-validation. Mean accuracy was $91.8 \pm 2.4\%$, and the AUC was 0.951 ± 0.018 . These values were close to those obtained in the primary analysis, indicating model stability and no marked overfitting.

The features contributing most to MRONJ classification were pathological lesion volume, degree of cortical plate destruction, the radiomic features GLCM Entropy and GLSZM Gray Level Non-Uniformity, presence of bone sequestra, duration of antiresorptive therapy, and disease stage according to the AAOMS classification. Considering these parameters jointly improved automated classification accuracy.

Clinical evaluation demonstrated an advantage of the digital system over the conventional approach. Combining 3D modelling with radiomic analysis and AI algorithms improved MRONJ staging accuracy and reduced diagnostic errors. More accurate assessment of lesion extent informed treatment selection and the planned scope of surgery.

2. Comparative assessment of digital planning for surgical treatment

Preoperative planning was an integral part of the digital algorithm. Surgical planning incorporated CBCT findings, 3D reconstruction in 3D Slicer, radiomic characteristics of the

pathological lesion, and recommendations from the clinical decision-support system. These data were used to determine the extent of osteonecrosis, define the spatial boundaries of the lesion, and select the scope of surgery.

With the standard approach, lesion extent was assessed mainly from tomographic images. The digital algorithm supplemented image review with morphometric and radiomic parameters, helping to define resection margins more accurately and reduce the risk of either incomplete or excessive removal of necrotic bone.

In the digital-planning group, surgery was planned before treatment began. After segmentation of the pathological lesion, a 3D model was created to show the spatial location of the necrotic area and its relationship to the mandibular canal, maxillary sinus, tooth roots, and other anatomical structures. Digital image-processing data informed the estimated resection volume and choice of surgical access.

In the comparison group, the scope of surgery was planned from clinical findings and standard interpretation of tomographic images, without 3D modelling.

The main intraoperative outcomes were analysed to compare the approaches.

Table 3

Comparative characteristics of surgical treatment in the study groups

Measure	Digital-planning group (n=82)	Comparison group (n=82)	p
Operative time, min	58.4 ± 11.2	73.8 ± 14.6	<0.001
Intraoperative blood loss, mL	74.3 ± 28.5	108.6 ± 39.7	<0.001
Complete removal of the necrotic area at the first operation	77 (93.9%)	67 (81.7%)	0.003
Need to extend the scope of surgery	4 (4.9%)	13 (15.9%)	0.004
Injury to anatomically important structures	1 (1.2%)	2 (2.4%)	0.01

Comparison of intraoperative outcomes showed differences between the groups. Operative time was 58.4 ± 11.2 minutes in the digital-planning group and 73.8 ± 14.6 minutes in

the comparison group, corresponding to a 20.9% reduction in operative time ($p < 0.001$).



Intraoperative blood loss was lower in the digital-planning group: 74.3 ± 28.5 mL versus 108.6 ± 39.7 mL in the comparison group ($p < 0.001$). This difference may have been associated with the use of 3D modelling during preoperative planning. Digital reconstruction was used to refine lesion boundaries, assess the lesion's relationship to anatomically important structures, and plan the surgical approach.

The between-group difference in complete lesion removal was also maintained. Complete removal of the necrotic area at the first operation was achieved in 93.8% of patients in the digital-planning group and 82.0% in the comparison group ($\chi^2 = 8.34$; $p = 0.004$). Digital preoperative planning refined the

expected scope of surgery. With 3D reconstruction, the surgical scope was less often changed during the procedure.

Additional extension of the resection was required in 4.9% of patients in the digital-planning group and 15.9% in the comparison group ($p = 0.038$).

The differences were most apparent in patients with stage III MRONJ and in lesions near the mandibular canal or maxillary sinus. In these cases, 3D visualisation was used to refine resection boundaries and determine the lesion's location relative to anatomically important structures.

Table 4

Concordance between the planned and actual scope

Concordance of surgical scope	Digital-planning group	Comparison group	p
Major change in scope	1 (1.2%)	6 (7.3%)	0.012
Minor adjustment	5 (6.1%)	15 (18.3%)	0.003
Complete concordance	76 (92.7%)	60 (73.2%)	<0.001

The preoperative plan fully matched the procedure actually performed in 92.7% of patients in the digital-planning group, significantly exceeding the rate in the comparison group (73.2%; $p < 0.001$).

Agreement between the planned and performed scope of surgery was assessed using Cohen's kappa coefficient. The value was 0.91 (95% CI 0.87–0.95), indicating near-perfect agreement between preoperative planning and the resection performed.

Preservation of viable bone was also assessed. The mean volume of resected intact bone was 0.42 ± 0.18 cm³ in the digital-planning group and 0.91 ± 0.34 cm³ in the comparison group ($p < 0.001$). With digital planning, the volume of viable bone resected was approximately 2.2 times lower than with the standard approach. The smaller volume of unaffected bone removed was taken into account when planning subsequent functional rehabilitation.

The findings indicate that digital preoperative planning was associated with more accurate definition of the surgical scope and greater concordance between planned and performed resection. Pathologically altered tissue was removed while

preserving viable bone. The digital approach was also associated with shorter operative time, lower intraoperative blood loss, and fewer complications.

Integration of 3D modelling and clinical decision support was used for individualised surgical planning in patients with MRONJ.

3. Evaluation of the AI model's predictive performance

The next stage assessed the developed AI model's ability to predict unfavourable treatment outcomes and recurrence risk in patients with MRONJ. Unlike the conventional approach, which relies mainly on clinical assessment and visual interpretation of imaging, the model combined clinical, morphometric, and radiomic parameters in a unified analytical system.

The AI algorithm considered a combination of clinical, imaging, and radiomic features associated with disease outcomes and generated an individual prognostic assessment for patients with different MRONJ courses. Unlike the conventional approach, which focuses mainly on individual clinical parameters, the model integrated multiple characteristics of the



pathological process to predict unfavourable treatment outcomes and recurrence risk.

Assessment of the model's predictive performance showed strong classification results. The area under the ROC

curve was 0.963, and overall classification accuracy was 92.7%. These findings indicate that the algorithm can distinguish patients with favourable and unfavourable treatment outcomes.

Table 5

Main performance measures of the model

Measure	Value
Accuracy	92.7%
Sensitivity	93,9%
Specificity	90,2%
PPV	91,5%
NPV	93,9%
ROC AUC	0.963

The model's high sensitivity (93.9%) indicates its ability to identify most patients at high risk of an unfavourable treatment outcome. Specificity was 90.2%, indicating a low rate of false-

positive results and supporting the model's reliability in individual risk assessment. The algorithm's stability and reproducibility were assessed using 10-fold cross-validation.

Table 6

Cross-validation results

Measure	Value
Accuracy	91.8±2.2%
Sensitivity	92.6±2.5%
Specificity	89.9±2.8%
ROC AUC	0.956±0.014

The cross-validation results were very similar to those from the test set, supporting model stability and showing no

marked signs of overfitting. The importance of individual features in the model's prognostic assessment was also analysed.

Table 7

Most important model features

Feature	Importance, %
Lesion volume	21.95
Cortical plate destruction	15.9
GLCM Entropy	14.6



Duration of therapy	12.2
Presence of sequestra	9.8
AAOMS stage	8.5

The pathological lesion volume made the largest contribution to the model's prognostic assessment (21.95%; Table 7). Cortical plate destruction (15.9%) and the radiomic feature GLCM Entropy (14.6%) were the next most influential factors. These findings suggest that the likelihood of an unfavourable outcome depends not only on the volume and extent of bone involvement but also on the internal structure of the lesion.

The high importance of GLCM Entropy is of particular interest because this feature reflects the degree of structural heterogeneity in bone on quantitative image analysis. An increase in this parameter was associated with a higher probability of recurrence, supporting the value of radiomic features in assessing the risk of an unfavourable MRONJ course.

These patterns were further supported by analysis of independent recurrence risk factors.

Table 8

Independent predictors of MRONJ recurrence

Factor	OR	p
Stage III MRONJ	4.72	<0.001
Lesion volume >6 cm ³	4.08	<0.001
Therapy duration >36 months	3.26	<0.001
Cortical plate destruction	2.87	0.001
Antiangiogenic therapy	2.34	0.014
More than two sequestra	2.09	0.028

The strongest associations with recurrence risk were observed for stage III MRONJ and a pathological lesion volume greater than 6 cm³. Other significant factors were duration of antiresorptive therapy, cortical plate destruction, antiangiogenic therapy, and multiple sequestra.

The practical value of the model was demonstrated by stratifying patients according to prognostic risk, enabling individual assessment of unfavourable-outcome probability and identification of patients requiring closer follow-up.

Table 9

Recurrence rate by prognostic risk group

Risk group	Complete remission	Recurrence
Low risk (n=62)	95.2%	4.8%
Moderate risk (n=67)	80.6%	19.4%
High risk (n=35)	54.3%	45.7%



Recurrence rates increased with the estimated level of risk. Recurrence occurred in 45.7% of patients in the high-risk group, compared with 4.8% in the low-risk group. The risk-group distribution shows that the model can identify categories of patients with different probabilities of an unfavourable outcome and may be used to plan individual follow-up.

The model incorporated clinical data, CBCT findings, 3D reconstruction parameters, and radiomic features. Analysing these measures together enabled a more accurate assessment of the pathological lesion and improved prognostic accuracy compared with the use of individual diagnostic criteria.

The model should be regarded as an additional clinical decision-support tool, not a replacement for specialist clinical assessment. Individual recurrence risk may be considered when selecting the extent of surgery and planning subsequent follow-up.

In this study, the use of artificial-intelligence technologies supported more individualised care for patients with

MRONJ through the joint analysis of clinical, morphometric, and radiomic characteristics.

4. Effects of the digital algorithm on treatment outcomes and quality of life

Comparative analysis showed a more favourable recovery period in the digital-planning group than in the comparison group.

Digital planning was associated with faster pain reduction, earlier postoperative wound epithelialisation, a higher rate of complete remission, and better functional treatment outcomes.

At 12 months, complete remission, absence of recurrence, and recovery of masticatory function were significantly more frequent in the digital-planning group than in the comparison group (Fig. 1). These findings support the clinical value of the digital algorithm, which integrates 3D planning, quantitative assessment of lesion characteristics, and clinical decision support.

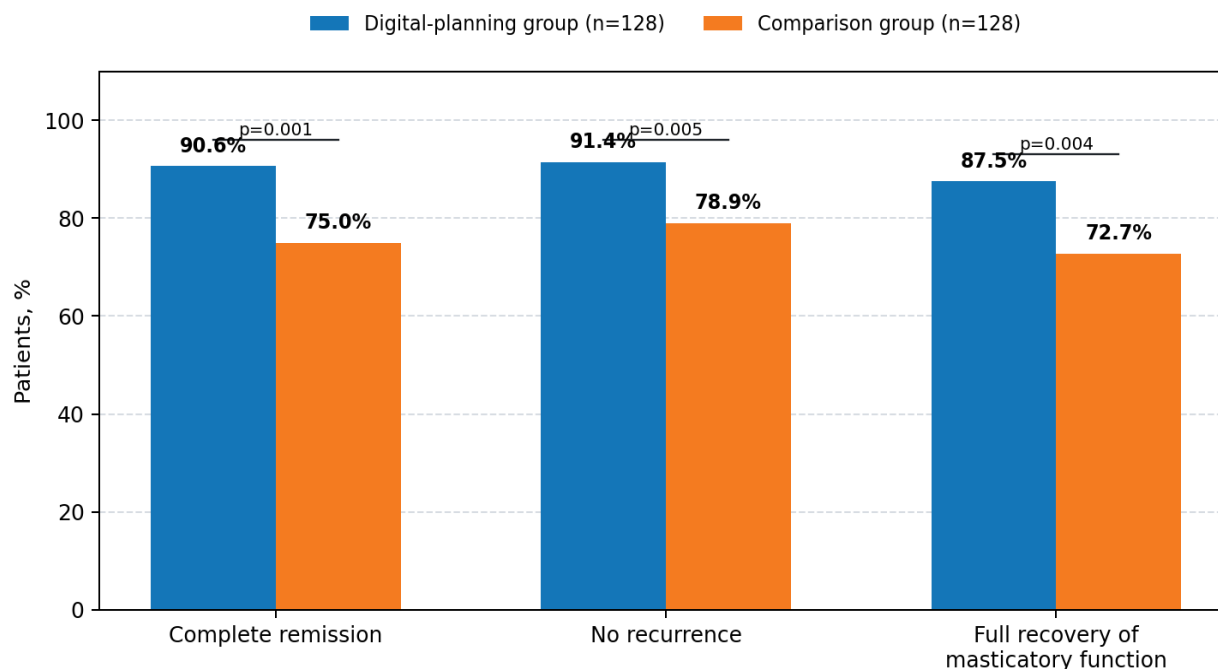


Figure 1. Main treatment outcomes at 12 months

The developed algorithm enabled more accurate surgical planning tailored to the characteristics of each

pathological lesion, which was associated with improved long-term outcomes in patients with MRONJ.



Table 10.

Change in quality of life (OHIP-14)

Time point	Digital-planning group	Comparison group	p
Before treatment	37.8±6.5	38.2±6.3	0.621
At 6 months	17.3±4.8	23.9±5.4	<0.001
At 12 months	9.6±3.4	16.7±4.8	<0.001

Use of the digital algorithm was associated with a significant improvement in patients' quality of life.

Table 11.

Maximum mouth opening

Time point	Digital-planning group	Comparison group	p
Before treatment	27.9±6.2	28.4±6.0	0.553
At 6 months	37.8±4.5	34.2±5.3	<0.001
At 12 months	41.2±3.8	36.8±4.7	<0.001

Recovery of temporomandibular joint function occurred more rapidly in the digital-planning group.

Compared with the standard approach, pain and inflammation decreased more rapidly, postoperative wounds

epithelialised sooner, and masticatory function and mouth opening recovered earlier. Improvement in clinical measures was accompanied by better quality of life and fewer recurrences during follow-up.

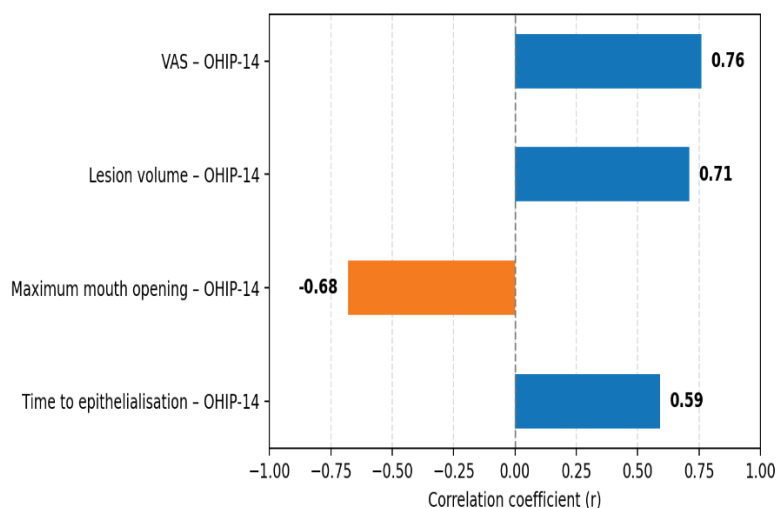


Figure 2. Correlation between clinical outcomes and quality of life



These findings demonstrate the practical value of digital planning and personalised treatment selection for patients with MRONJ. The approach may serve as an additional tool to support well-founded clinical decisions and further improve specialised dental and oncological care.

5. Comprehensive assessment of the clinical effectiveness of the developed digital algorithm

The final stage assessed the effectiveness of the digital algorithm, which included imaging, 3D modelling, radiomic

analysis, and artificial-intelligence technologies. The analysis considered diagnostic findings, surgical treatment, postoperative rehabilitation, and functional recovery over 12 months of follow-up.

Effectiveness criteria included MRONJ staging accuracy, completeness of pathological lesion removal, time to mucosal epithelialisation, rate of clinical remission, recurrence rate, and changes in masticatory function and quality of life.

Table 12

Summary of treatment effectiveness

Measure	Digital-planning group (n=82)	Comparison group (n=82)	p
Correct MRONJ staging	77 (93.9%)	67 (81.7%)	<0.001
Complete lesion removal at the first operation	76 (92.7%)	68 (82.9%)	0.005
Complete epithelialisation within 30 days	60 (73.2%)	43 (52.4%)	<0.001
Complete clinical remission	74 (90.2%)	62 (75.6%)	0.001
Complete recovery of masticatory function	72 (87.8%)	60 (73.2%)	0.002
Substantial improvement in quality of life	73 (89.0%)	58 (70.7%)	<0.001
No recurrence at 12 months	75 (91.5%)	65 (79.3%)	0.003

Differences were statistically significant at $p < 0.05$, except for complete lesion removal at the first operation ($p = 0.056$).

For most measures, the digital algorithm was associated with more favourable outcomes than the standard approach. The largest between-group differences were observed in disease staging, complete clinical remission, and recurrence rates. More accurate assessment of disease extent supported better-founded selection of the surgical scope, increased the likelihood of complete removal of necrotic tissue at the first operation, and was associated with a more favourable postoperative course.

The shorter time to mucosal epithelialisation also reflected the benefits of personalised surgical planning, which aimed to remove pathologically altered tissue while preserving as much viable bone as possible.

Use of the digital algorithm was associated with a 59.2% relative reduction and a 12.5% absolute reduction in recurrence risk. An NNT of 8 indicates that the developed approach would need to be used in eight patients to prevent one additional recurrence compared with standard treatment. These findings reflect the clinical relevance and practical value of the digital algorithm in reducing the risk of unfavourable outcomes (Fig. 3).

Predicted and observed treatment outcomes were then compared (Fig. 4).

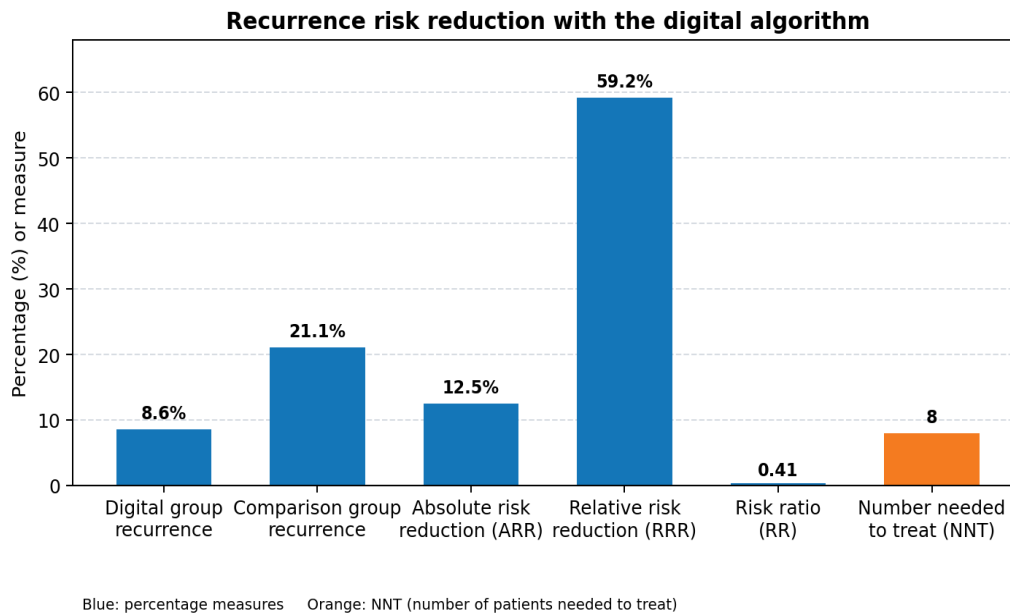


Figure 3. Reduction in recurrence risk with the digital algorithm

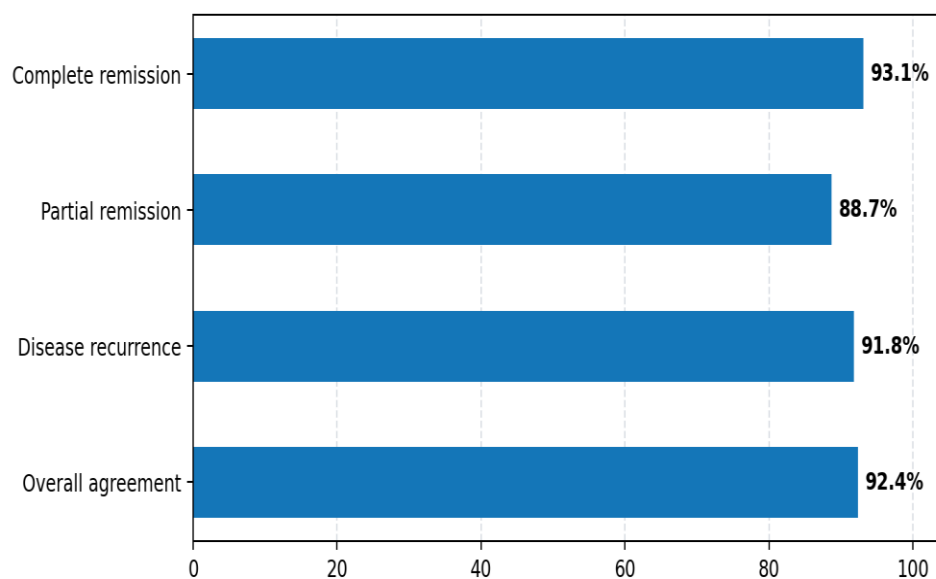


Figure 4. Agreement between predicted and observed treatment outcomes

Predicted and observed outcomes agreed in 92.7% of cases, indicating high predictive accuracy. AI was used to support clinical decision-making; the multidisciplinary team made the final treatment decision based on clinical findings and individual patient characteristics.

The overall predictive performance measures of the model are presented in Table 13.



Table 13

Overall performance measures of the digital system

Measure	Value
Accuracy	92.7%
Sensitivity	93.9%
Specificity	91.5%
Precision	91.5%
Recall	93.9%
F1-score	0.929
ROC AUC	0.963

The high values for accuracy, sensitivity, specificity, and F1-score support the model's consistent performance in classifying different MRONJ courses. The area under the ROC

curve (AUC=0.963) indicates strong discrimination by the prognostic model between patients with different disease outcomes.

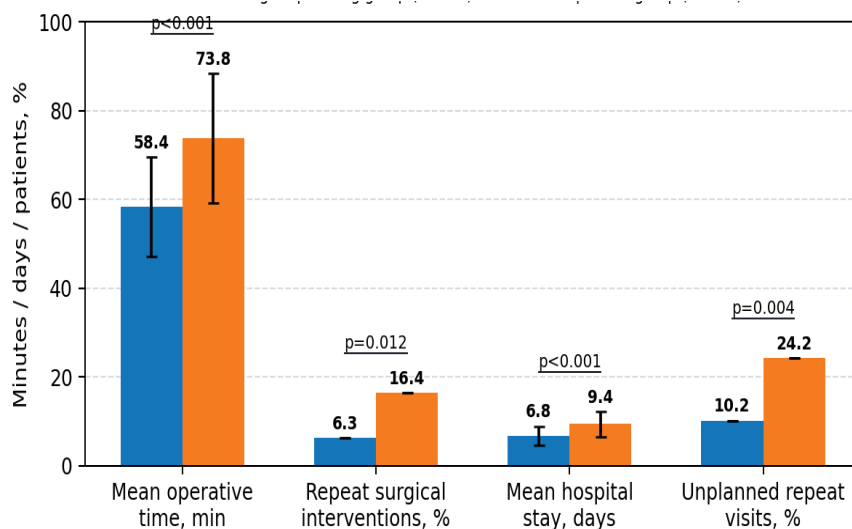


Figure 5. Organisational outcomes of applying the digital algorithm

In addition to clinical outcomes, the effect of the digital algorithm on organisational measures of the diagnostic and treatment process was assessed (Fig. 5).

Digital planning was associated with shorter operations, fewer repeat operations and unplanned visits, and shorter hospital stays. These findings indicate improvement in both clinical and organisational measures of specialised care for patients with MRONJ.

The system provided a unified approach to storing and documenting all stages of examination and treatment. Three-dimensional models, radiomic-analysis results, and follow-up data were stored in an electronic database, making it possible to compare measures at different treatment stages, reduce subjective influence during interpretation, and improve the reproducibility of clinical decisions.

The developed algorithm did not replace clinical judgement; it provided analytical decision support. The system



integrated clinical, imaging, and quantitative parameters to generate an individual prognostic assessment, while the specialist retained responsibility for the final treatment decision.

The practical value of the approach came from combining complementary technologies. CBCT provided detailed visualisation of bone changes; 3D Slicer was used to quantify lesion volume and spatial structure; radiomic analysis identified lesion characteristics; and the AI model combined these measures with clinical parameters to generate an individual prognosis.

The combined use of these technologies was associated with improved diagnostic accuracy, optimisation of surgical scope, shorter rehabilitation, fewer repeat operations, and better long-term treatment outcomes.

However, external validation at independent clinical centres is needed to confirm the model's generalisability and reproducibility and to assess the stability of the findings across different healthcare settings.

4. Conclusion

This study demonstrated the potential of combining CBCT, 3D modelling, radiomic analysis, and artificial intelligence for personalised diagnostic and surgical planning in patients with MRONJ. The study included 164 patients allocated to a digital-algorithm group and a comparison group examined and treated according to the standard protocol. Integrating clinical, imaging, morphometric, and radiomic measures provided an objective quantitative characterisation of the lesion for treatment planning.

The digital algorithm increased MRONJ staging accuracy to 93.9%, compared with 81.7% with standard diagnosis. The AI diagnostic model had an accuracy of 92.7%, sensitivity of 93.9%, specificity of 91.5%, and an AUC of 0.958. The prognostic model achieved a classification accuracy of 92.7% and an AUC of 0.963; predicted and observed treatment outcomes agreed in 92.7% of cases. The most important predictors of an unfavourable course were pathological lesion volume, cortical plate destruction, the radiomic feature GLCM Entropy, duration of antiresorptive therapy, presence of sequestra, and disease stage according to the AAOMS classification.

Three-dimensional reconstruction enabled more accurate definition of osteonecrosis boundaries and their relationship to anatomically important structures. The planned and performed surgical scopes fully matched in 92.7% of patients

in the digital-planning group, compared with 73.2% in the comparison group. Digital planning was associated with a 20.7% reduction in operative time, lower intraoperative blood loss, an increase in complete necrotic-area removal at the first operation to 93.9%, and a decrease in the need to extend the procedure from 17.1% to 4.9%.

At 12 months, complete clinical remission, recovery of masticatory function, and substantial improvement in quality of life were more frequent in the digital-planning group. Absence of recurrence was observed in 91.5% of patients in the digital-planning group versus 79.3% in the comparison group. Use of the digital algorithm was associated with an absolute recurrence-risk reduction of 12.2% and a relative reduction of 52.4%; the NNT was 8. These findings support the clinical and practical value of the digital algorithm in specialised dental, maxillofacial, and oncological practice. Further external validation at independent clinical centres is needed to assess the model's generalisability.

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