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CLINICAL RESEARCH

An AI-based tool for prosthetic crown segmentation serving automated intraoral scan-to-CBCT registration in challenging high artifact scenarios

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ABSTRACT

Statement of problem. Accurately registering intraoral and cone beam computed tomography (CBCT) scans in patients with metal artifacts poses a significant challenge. Whether a cloud-based platform trained for artificial intelligence (AI)-driven segmentation can improve registration is unclear.

Purpose. The purpose of this clinical study was to validate a cloud-based platform trained for the AI-driven segmentation of prosthetic crowns on CBCT scans and subsequent multimodal intraoral scan-to-CBCT registration in the presence of high metal artifact expression.

Material and methods. A dataset consisting of 30 time-matched maxillary and mandibular CBCT and intraoral scans, each containing at least 4 prosthetic crowns, was collected. CBCT acquisition involved placing cotton rolls between the cheeks and teeth to facilitate soft tissue delineation. Segmentation and registration were compared using either a semi-automated (SA) method or an AI-automated (AA). SA served as clinical reference, where prosthetic crowns and their radicular parts (natural roots or implants) were threshold-based segmented with point surface-based registration. The AA method included fully automated segmentation and registration based on AI algorithms. Quantitative assessment compared AA's median surface deviation (MSD) and root mean square (RMS) in crown segmentation and subsequent intraoral scan-to-CBCT registration with those of SA. Additionally, segmented crown STL files were voxel-wise analyzed for comparison between AA and SA. A qualitative assessment of AA-based crown segmentation evaluated the need for refinement, while the AA-based registration assessment scrutinized the alignment of the registered-intraoral scan with the CBCT teeth and soft tissue contours. Ultimately, the study compared the time efficiency and consistency of both methods. Quantitative outcomes were analyzed with the Kruskal-Wallis, Mann-Whitney, and Student *t* tests, and qualitative outcomes with the Wilcoxon test (all α=.05). Consistency was evaluated by using the intraclass correlation coefficient (ICC).

Results. Quantitatively, AA methods excelled with a 0.91 Dice Similarity Coefficient for crown segmentation and an MSD of 0.03 ±0.05 mm for intraoral scan-to-CBCT registration. Additionally, AA achieved 91% clinically acceptable matches of teeth and gingiva on CBCT scans, surpassing SA method's 80%. Furthermore, AA was significantly faster than SA (P<.05), being 200 times faster in segmentation and 4.5 times faster in registration. Both AA and SA exhibited excellent consistency in segmentation and registration, with ICC values of 0.99 and 1 for AA and 0.99 and 0.96 for SA, respectively.

Conclusions. The novel cloud-based platform demonstrated accurate, consistent, and time-efficient prosthetic crown segmentation, as well as intraoral scan-to-CBCT registration in scenarios with high artifact expression. (J Prosthet Dent 2025;134:191-198)

No conflict of interest.

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Clinical Implications

The AI-driven segmentation of prosthetic crowns on CBCT scans can diminish the impact of artifacts on the resulting 3-dimensional (3D) cast, thus enhancing the accuracy of the AI algorithms used for automated surface-based intraoral scan-to-CBCT registration. This functionality renders it a valuable tool for generating accurate 3D casts of both soft and hard tissues in preoperative digital dental implant planning.

The implementation of digital tools in implant dentistry has enhanced the prediction and accuracy of both dental implant planning and its guided placement.[1,2] Cone beam computed tomography (CBCT) has become an indispensable tool in implant dentistry, providing detailed 3-dimensional (3D) imaging for precise diagnosis, treatment planning, and surgical guidance.[3–5] However, relying solely on CBCT assessment is insufficient to capture all patient information because of its limitations in depicting soft tissue and detailed dental anatomy.[6] Therefore, an intraoral scan (IOS) must be registered with the CBCT scan to ensure visualization of both hard and soft tissues.[7–9]

The segmentation of CBCT with prominent metal artifact expression poses considerable challenges. Artifacts can originate from sources that include prosthetic crowns, dental implants, dental restorations, and orthodontic brackets[10,11] and may obscure the true dental anatomy, resulting in segmented crown anatomy from an CBCT scan that may not accurately reflect those observed in IOSs.[12,13] Consequently, the IOS-to-CBCT registration process typically entails identifying common points within segmented natural tooth crowns or prosthetic crowns derived from CBCT scans, as well as the crowns captured by IOSs. Nevertheless, when the CBCT scans exhibit artifacts, locating these shared points between the 2 distinct 3D datasets becomes challenging.[14–17]

Artificial intelligence (AI) has recently been incorporated into CBCT segmentation, demonstrating its ability to produce high-quality segmentations of CBCT scans even when dealing with prominent artifacts from sources such as dental devices.[11,18–23] Additionally, AI has been implemented in the IOS-to-CBCT registration process, autonomously performing this task without human intervention.[9,24–27]

As efforts to integrate AI-based solutions into digital workflows, there remains a lack of evidence concerning the implementation and evaluation of clinically applicable AI-driven tools for accurately segmenting prosthetic crowns on CBCT and registering IOSs with CBCT scans, especially in scenarios with high metal artifact expression.[28] The aim of this study was to validate an AI-based tool for prosthetic crown segmentation on CBCT scans and IOS-to-CBCT registration in scenarios with significant artifact expression (containing at least 4 prosthetic crowns) by comparing its performance with a semi-automated approach (reference group) regarding accuracy, time efficiency, and consistency. The null hypothesis was that an AI-based approach to prosthetic crown segmentation and subsequent IOS-to-CBCT registration would have the same accuracy, time efficiency, and consistency as the semi-automated approach.

MATERIAL AND METHODS

This retrospective study received ethical approval from the Local Ethical Review Board at UZ Leuven Hospital (Leuven, Belgium) under reference number s66447. The study adhered to the principles outlined in the International Conference on Harmonization Guidelines for Good Clinical Practice, the Declaration of Helsinki, the Oviedo Convention, and relevant legal requirements. All patient data were anonymized to ensure confidentiality.

Thirty time-matched CBCT and jaw IOSs with prosthetic crowns were retrieved from the imaging database at UZ Leuven Hospital in Belgium between 2016 and 2023. The dataset included 15 mandibular and 15 maxillary scans of patients aged 30 to 80 (average age 62.6) who needed dental implant placement. Cotton rolls had been placed in the buccal and labial sulcus between the cheeks and teeth during CBCT acquisition to enhance soft tissue delineation. CBCT scans were acquired by using a CBCT device (NewTom VGI Evo; NewTom) with different fields of view (8×8, 10×10, 12×15, 16×16, and 24×19 cm) and voxel sizes (0.30, 0.25, and 0.10 mm^3). IOS data were acquired by using an intraoral scanner (TRIOS 3; 3Shape A/S).

Inclusion criteria required scans with a minimum of 6 teeth present, including at least 4 prosthetic crowns (on teeth, implants, or pontics), made from radiopaque materials such as zirconia, porcelain, or metal. Exclusion criteria included severe motion artifacts and radiolucent crowns. The dataset was divided into 2 groups: low artifact expression (15 scans with 4 to 6 crowns); and high artifact expression (15 scans with more than 6 crowns). CBCT scans were exported in digital imaging and communication in medicine (DICOM) format, and IOSs in standard tessellation language (STL) format.

Prosthetic crowns in each CBCT scans were segmented using 2 approaches. For the semi-automated segmentation (SAS) (clinical reference), the CBCT-DICOM files and IOSs were imported into an image processing software program (Materialise Mimics; Materialise NV). Manual registration between CBCT scans and IOSs was done by a dentist experienced in prosthodontics (S.A.) and verified by a dentomaxillofacial

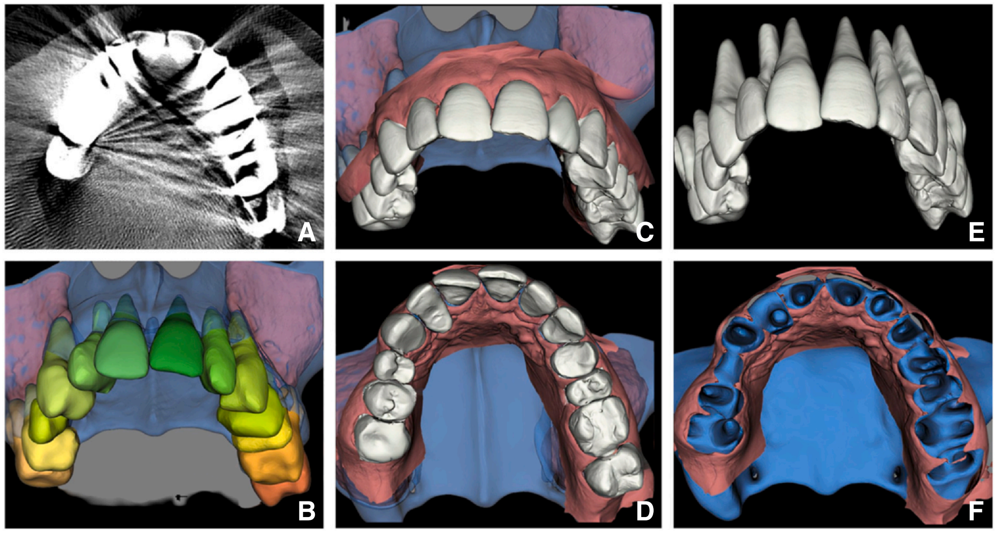

Figure 1. AI-based segmentation and registration of CBCT with high metal artifact expression and maxillary IOS. A, CBCT showing artifact sources (crowns, implants, and dental restorations); B, AI-based segmentation of teeth, crowns, and implants; C, Frontal view of CBCT and IOS registration; D, Occlusal view of the registration; E, AI-based fusion of crowns (CBCT and IOS) and roots from CBCT; F, Soft tissue relation to underlying bone after virtual teeth and implant extraction. AI, artificial intelligence; CBCT, cone beam computed tomography; IOS, intraoral scan.

radiologist (R.C.F.) by checking the peripheries of the IOS soft and hard tissues on the CBCT scans. Prosthetic crown segmentation, including natural roots, implants, and pontics, was achieved by using a 1500 to 7000 HU threshold and refined across CBCT planes (sagittal, axial, and coronal) to ensure precise alignment with the IOS periphery.[29]

For the AI-automated segmentation (AAS), DICOM files were uploaded to a cloud-based AI platform (Relu Creator; Relu BV). This platform, previously trained for segmenting prosthetic crowns,[11] automatically segmented the prosthetic crowns along with their radicular parts by using deep learning algorithms (Fig. 1). This process utilized two 3D U-networks: one for initial rough segmentation and another to refine the segmentation of the prosthetic crowns. Finally, in both methodologies, a virtual STL cast of each segmented prosthetic crown (crown on tooth and implant or pontic) was generated and exported in STL file format.

IOS-to-CBCT registration involved a surface-based approach, where the IOS was uploaded onto the previously segmented CBCT cast. This registration process used 2 distinct methods. For the semi-automated registration (SAR) (clinical reference), in an image processing software program (Materialise Mimics; Materialise NV) and after segmenting the prosthetic crowns, the region of interest was expanded to include all natural tooth crowns in the CBCT scans. A definitive cast for each jaw was then created, incorporating segmented tooth crowns and prosthetic crowns along with their respective roots or implants. The SAR process involved selecting exact points (2 anterior and 2 posterior) to align the CBCT and IOS casts.[30,31]

For the AI-Automated registration (AAR), in the cloud-based AI platform (Relu Creator; Relu BV), the AAR process began with the simultaneous uploading of CBCT scans and IOSs. The platform automatically segmented teeth and prosthetic crowns, along with their corresponding roots or implants from CBCT scans, as well as crowns from IOS.[11,32,33] The initial IOS-to-CBCT registration was performed by using deep learning networks, followed by refinement through an iterative closest point (ICP) approach. This refinement used predicted points from the segmented crowns in IOSs and their corresponding points on the CBCT cast, all without human intervention (Fig. 1). Two registered IOSs (R-IOSs) per situation (1 from each approach) were exported as STL files for further comparative analysis.

A total of 150 prosthetic crowns from 30 CBCT scans (66 on teeth, 52 on implants, and 32 pontics) were selected to compare SAS and AAS by using a voxel-wise analysis of each segmented crown (Supplemental Table 1, available online). STL files of the segmented crowns and R-IOSs, generated by both methods, were imported into a 3D design software program (Materialise 3-matic; Materialise NV) for surface analysis. Median surface deviation (MSD) and root mean square (RMS) were used to assess overlap between the segmented crowns and R-IOSs, with a score of zero indicating complete overlap.

Two operators (B.E., S.A.), each with over 5 years of prosthetic dentistry experience, evaluated the segmentation quality of each method, refining the crowns together until consensus was reached. For registration, 1 operator (B.E.) assessed whether the teeth and gingiva from R-IOS matched or deviated from the reference

Table 1. Accuracy metrics (median ±IQR) obtained from comparison of AI-automated and semi-automated approaches (clinical reference) for prosthetic crown segmentation

	AI-automated Segmentation Versus Semi-automated Segmentation				
Metric	**Crown + Tooth n=66**	**Crown + Implant n=52**	**Pontic n=32**	**Entire Sample n=150**	***P***
Accuracy	0.96 ±0.01 A	0.94 ±0.03 B	0.90 ±0.02 B	0.96 ±0.03	<.001*
Precision	0.94 ±0.06 A	0.88 ±0.06 B	0.94 ±0.07 AB	0.93 ±0.07	.02*
Recall	0.92 ±0.04 A	0.87 ±0.10 B	0.75 ±0.03 C	0.89 ±0.07	<.001*
DSC	0.93 ±0.02 A	0.87 ±0.04 B	0.84 ±0.04 B	0.91 ±0.07	<.001*
IOU	0.87 ±0.04 A	0.77 ±0.06 B	0.72 ±0.06 B	0.84 ±0.11	<.001*
95% HD (mm)	0.79 ±0.23 A	1.37 ±0.75 B	1.33 ±0.46 B	0.92 ±0.40	<.001*
MSD (mm)	0.09 ±0.08 A	0.35 ±0.17 B	0.38 ±0.07 B	0.18 ±0.28	<.001*
RMS (mm)	0.34 ±0.12 A	0.58 ±0.21 B	0.64 ±0.19 B	0.42 ±0.26	<.001*

DSC, dice similarity coefficient; HD, Hausdorff distance; IOU, intersection over union; IQR, interquartile range; MSD, median surface deviation; RMS, root mean square.

* Indicates significant difference among prosthetic crown types, based on Kruskal–Wallis test and Conover post hoc analysis. Different uppercase letters signify statistically significant difference (*P*<.05).

gingival contour and tooth boundaries on the CBCT scans.[34,35] The registered IOS-CBCT cast of the maxilla or mandible was divided into 3 zones: anterior, posterior right, and posterior left. Each zone was graded on a 3-point scale: 0 for clinically acceptable matching, where IOS soft tissue and teeth were well aligned with the gingival contour, tooth, and crown boundaries on the CBCT scans, while accounting for the inherent effects of beam hardening (hypodense bands, hyperdense streaks, and blooming) caused by high-density materials on CBCT scans[11]; 1 for minor deviation, where IOS soft tissue and teeth showed slight misalignment with the gingival contour, teeth, and crown boundaries on CBCT scans; 2 for major deviation (clinically unacceptable), where IOS soft tissue and teeth were completely misaligned with the gingival contour, tooth, and crown boundaries on CBCT scans. The average score across all regions was then recorded.[9] To verify reliability in the qualitative evaluation, 20% of jaw scans were re-evaluated by the same operator 30 days later.

Prosthetic crown segmentation time (from DICOM upload to crown export) and IOS-to-CBCT registration time (from IOS upload to R-IOS export) were measured using a stopwatch. A 20% subsample was resegmented and reregistered with AA and SA to evaluate consistency by comparing results with the initial package via color-coded part-comparison mapping.

A statistical software program (GraphPad Prism; Dotmatics) was used for data analysis. Descriptive statistics included frequencies and percentages for qualitative data. For parametric quantitative data, the mean and standard deviation (SD) were reported, while the median and interquartile range (IQR) were used for nonparametric data. Normality was assessed by using the Shapiro–Wilk test. The Kruskal–Wallis test compared segmentation accuracy across crown types, while the Mann–Whitney test evaluated registration accuracy. Intra-observer agreement was measured with weighted kappa (κ) by following the Landis and Koch scale.[36] The Wilcoxon test analyzed qualitative differences in registration, and the Student *t* test assessed time and consistency. ICC measured consistency between AA and SA, with <0.50 poor, 0.50 to 0.75 moderate, 0.75 to 0.90 good, and >0.90 excellent (α=.05).[37]

RESULTS

Table 1 summarizes the accuracy metrics by comparing AAS and SAS across the entire sample and all crown types. A significant difference in segmentation was observed between AAS and SAS among all types of crowns (*P*<.05). When considered across the entire dataset, AAS demonstrated a high DSC of 0.91 ±0.07 and a low MSD value of 0.18 ±0.28 mm compared with SAS, indicating a high level of similarity between both methods.

Table 2 presents the surface-based comparison between AAR and SAR. Across the entire dataset, AAR

Table 2. Surface-based metrics (median ±IQR) obtained from comparison of AI-automated and semi-automated (clinical reference) approaches for intraoral scan-to-CBCT registration

	AI-automated Registration versus Semi-automated Registration			
Metric	**≤6 Prosthetic Crowns n=15**	**>6 Prosthetic Crowns n=15**	**Entire Sample n=30**	***P***
MSD (mm)	0.03 ±0.02	0.05 ±0.08	0.03 ±0.05	.06
RMS (mm)	0.09 ±0.04	0.17 ±0.13	0.12 ±0.14	<.001*

IQR, interquartile range; MSD, median surface deviation; RMS, root mean square.

* Indicates significant difference in registration between scans with ≤6 prosthetic crowns and scans with >6 prosthetic crowns, as indicated by Mann–Whitney test (*P*<.05).

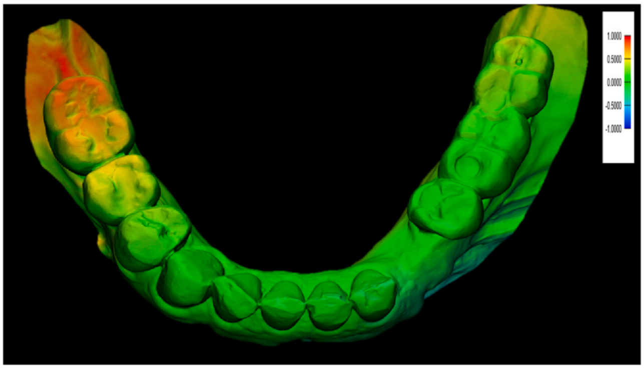

Figure 2. Color-coded maps comparing AI-based and semi-automated IOS-to-CBCT registration of mandibular scan with prosthetic crowns on natural teeth and implants. *Green* indicates perfect alignment between both approaches. *Red* denotes 1-mm deviations in right posterior area. Color-coded legend based on part comparison analysis using −1 mm to 1 mm scale. AI, artificial intelligence; CBCT, cone beam computed tomography; IOS, intraoral scan.

demonstrated minimal MSD values of 0.03 ±0.05 mm and RMS values of 0.12 ±0.14 mm using SAR as the clinical reference (Fig. 2). These findings indicate a high level of agreement between the 2 approaches. However, AAR showed greater deviation in scans containing more than 6 crowns, with an RMS value of 0.17 ±0.13 mm compared with an RMS value of 0.09 ±0.04 mm in scans with 6 or fewer crowns.

Refinements were necessary in 10% of the crowns (n=15 crowns) segmented by using the AA approach, primarily in the cervical area between the prosthetic crowns and the roots or implants. In terms of registration, there was substantial intra-operator agreement (κ=0.77) in the qualitative evaluation of the IOS-to-CBCT registration. Figure 3 illustrates the qualitative evaluation of IOS soft and hard tissue boundaries on CBCT scans. Table 3 presents the percentage and frequency of scoring evaluations for both AAR and SAR. A significant difference was observed in the scoring evaluation between the AAR and SAR for the entire sample (*P*=.04). AAR achieved a higher percentage of clinically acceptable matching (91%) for IOS soft and hard tissue boundaries on CBCT scans compared with SAR, which achieved 80%.

The average time for AAS of prosthetic crowns per crown was significantly faster, being nearly 200 times more efficient compared with SAS, while in the registration process, AAR was around 4.5 times faster than SAR (*P*<.001) (Fig. 4). Table 4 presents the consistency metrics and ICC values for each method. Significant differences were observed between AA and SA in both segmentation and registration (*P*<.05). AA achieved ICC values of 0.99 for segmentation and 1 for registration, surpassing SA's 0.99 and 0.96, highlighting AA's better consistency in patients' CBCT scans with metal artifacts.

DISCUSSION

The integration of AI has revolutionized preoperative planning in implant dentistry, significantly reducing work time and minimizing the need for operator input.[18,28] However, the effectiveness of AI in clinical settings for implant dentistry has not been fully

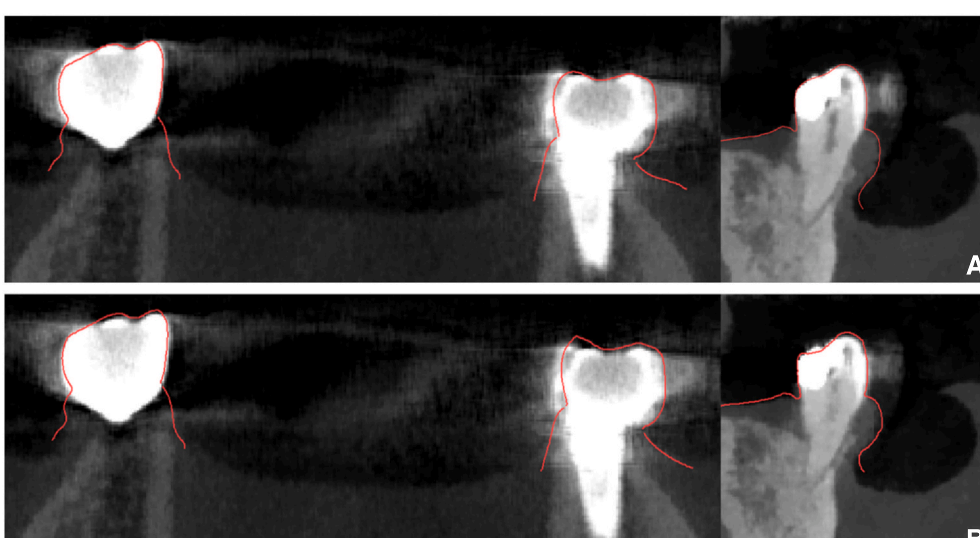

Figure 3. Qualitative assessment of mandibular IOS soft and hard tissue registration on CBCT, displayed in coronal and sagittal sections. *Red line* indicates boundaries of IOS soft and hard tissue. A, Clinically acceptable matches for IOS registered to CBCT using semi-automated approach. B, Minor deviation for same IOS registered to CBCT using AI-automated approach. No major deviations observed for either method. AI, artificial intelligence; CBCT, cone beam computed tomography; IOS, intraoral scan.

Table 3. Absolute (n) and relative (%) frequency of matching and deviation in intraoral scan-to-CBCT registration for AI-automated and semi-automated registration approaches

Method	SAR	AAR	SAR	AAR	SAR	AAR
	n (%)					
Prosthetic Crowns no.	≤6 n=15		>6 n=15		Entire sample n=30	
Clinically acceptable	38 (85%)	45 (100%)	34 (76%)	37 (78%)	72 (80%)	82 (91%)
Minor deviation	7 (15%)	0 (0%)	11 (24%)	8 (22%)	18 (20%)	8 (9%)
Major deviation	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
P					.04*	

AAR, AI-automated registration; SAR, semi-automated registration.

* Indicates significant difference between both registration methods across entire sample (Wilcoxon test) (*P*<.05).

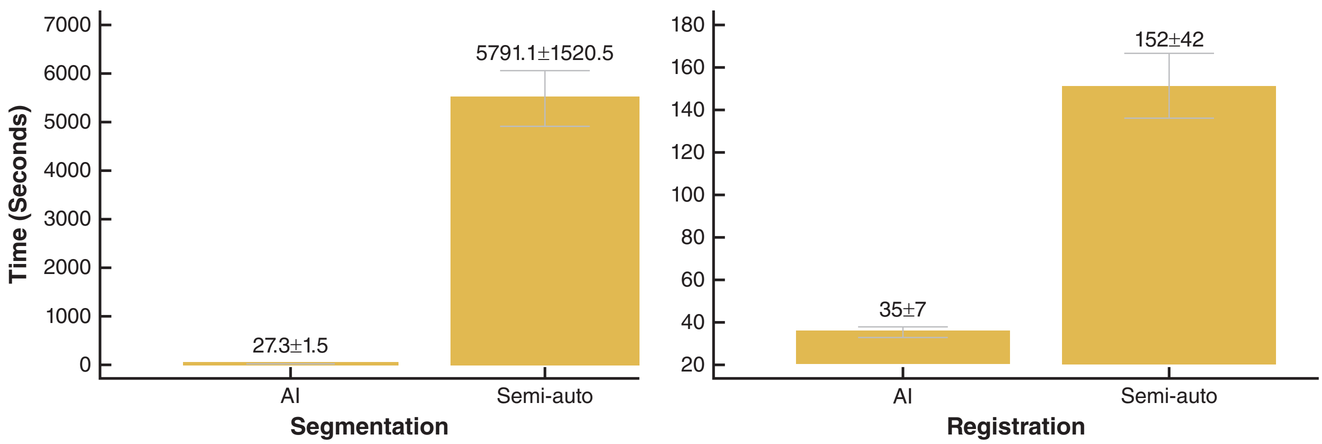

Figure 4. Time consumption comparison between AI-automated and semi-automated approaches in segmenting prosthetic crowns and subsequent IOS-to-CBCT scans registration. AI, artificial intelligence; Semi-auto, semi-automated approach; CBCT, cone beam computed tomography; IOS, intraoral scan.

established.[4,18] The present study focused on automating an essential step in digital preoperative planning, IOS-to-CBCT registration, even when the CBCT scans exhibit significant artifact expression. These scenarios are challenging because artifacts can obscure or distort anatomic landmarks in CBCT scans, thereby complicating the registration process between CBCT scans and IOSs. The null hypothesis that an AI-based approach to prosthetic crown segmentation and subsequent IOS-to-CBCT registration would have the same accuracy, time efficiency, and consistency as the semi-automated approach was rejected, as a significant difference between AA and SA was found in both prosthetic crown segmentation and subsequent IOS-to-CBCT registration.

The quantitative evaluation of AAS for prosthetic crowns showed similar performance (DSC=0.91 ±0.07) compared with SAS over the entire sample. AAS performed well for crowns on natural teeth (DSC=0.93 ±0.02), while the performance was slightly lower for crowns on implants (DSC=0.87 ±0.04) and even lower for pontics (DSC=0.84 ±0.04). This variation was associated with the increased presence of artifacts in CBCT scans with implants, which affected the segmentation quality. For pontics, the challenge was exacerbated by the combination of radiopaque and radiolucent materials in the crowns.[11] In addition, the quantitative analysis of registration accuracy showed a strong agreement between AAR and SAR, with an RMS value of 0.12 mm, consistent

Table 4. Consistency metrics (mean ±SD) for both AI-automated and semi-automated approaches for prosthetic crown segmentation and intraoral scan-to-CBCT registration

Metrics	Segmentation			Registration		
	SA	AA	P value	SA	AA	*P*
MSD (mm)	0.03 ±0.03	0.07 ±0.04	*P*=.007*	0.00 ±0.00	0.02 ±0.01	.002*
RMS (mm)	0.12 ±0.09	0.12 ±0.07	*P*=.057	0.01 ±0.01	0.09 ±0.05	.008*
ICC	0.99	0.99		0.96	1	

AA, AI-automated approach; ICC, intraclass correlation coefficient; MSD, median surface deviation; RMS, root mean square; SA, semi-automated approach; SD, standard deviation.

* Indicates significant difference as determined by paired Student *t* test (*P*<.05).

with previous studies. Preda et al[27] reported deviations in AI-based IOS-to-CBCT registration with an RMS value of 0.21 mm, while Elgarba et al[9] reported an RMS value of 0.19 mm. However, the design of these studies differed from the present investigation in that they compared AI-based IOS-to-CBCT registration with a SA approach for natural dentitions without metal artifacts.

Qualitative analysis indicated that 10% of the crowns segmented using the AA approach required refinement in the cervical region, likely because of threshold differences between different crown materials (metal or ceramic) and natural roots or implants.[11] In registration, AA achieved a higher rate of clinically acceptable matches (91%) and a lower rate of minor deviations (9%) compared with SA (80% and 20%, respectively). The largest difference was seen in scans with 6 or fewer prosthetic crowns, where AA had 100% clinically acceptable matches compared with 85% for SA. In scans with more than 6 prosthetic crowns, both methods had nearly identical clinically acceptable match rates (78% for AA and 76% for SA). This discrepancy can be attributed to the increased number of artifact sources, which can affect the quality of registration, as reported by Flügge et al.[14]

AI integration significantly accelerates virtual patient creation, nearly 200 times faster for segmentation and 4.5 times faster for registration, highlighting its transformative impact on preoperative planning. These results are consistent with those of previous studies, including those by Piao et al[24] and Elgarba et al[9,11] that reported significant reductions in IOS-to-CBCT registration time with the use of AI.[9,11,22–24] Crown segmentation consistency was comparable between AA and SA (ICC=0.99), with AI achieving segmentation 200 times faster. For registration, AI demonstrated better consistency (ICC=1) compared with SA (ICC=0.96), which was attributed to its improved performance in detecting numerous common points between IOS and CBCT casts, thereby reducing deviations. In contrast, the SA relies on fewer matched points, and human corrections in CBCT slices may further affect registration accuracy.[30,31]

A major strength of this study was the clinical validation of a novel AI-based cloud platform for segmenting prosthetic crowns with natural teeth, implants, or pontics on CBCT scans and facilitating IOS-to-CBCT registration. This platform, which is part of an AI-driven dental implant planning project, has also been validated for segmenting maxillofacial structures and registering imaging modalities.[9,21–23] This study validated the segmentation of prosthetic crowns on CBCT scans and subsequent IOS-to-CBCT registration in high metal artifact scenarios, including scans with 6 or fewer crowns and those with more than 6 crowns. AA results were compared with a clinical reference established using the SA approach and expert verification, which involved accurate qualitative delineation with soft and hard tissue references on CBCT scans.[34,35]

Caution should be exercised when extrapolating these findings to datasets from other CBCT and IOS devices, as their technical parameters may differ. Scans with fewer than 6 teeth were excluded because of registration challenges, highlighting the need to identify alternative anatomic landmarks for IOS-to-CBCT registration.[38] Finally, although this study validated the AI approach by comparing it with the expert method that served as the clinical reference, it may ultimately rely on subjective human judgment. To increase the robustness of AI validation, future studies should consider multicenter designs that include different CBCT and IOS devices, involve clinicians with different levels of expertise, and account for a wide range of dentition patterns and artifact sources to provide a more comprehensive evaluation of AI performance in different clinical contexts.

CONCLUSIONS

Based on the findings of this clinical study, the following conclusions were drawn:

1. The currently tested cloud-based AI tool demonstrated accurate, time-efficient, and consistent prosthetic crown segmentation on CBCT scans, as well as IOS-to-CBCT registration.
2. Integration of this AI-driven tool into the digital dental workflow can improve the efficiency of patient-specific preoperative and prosthetic treatment planning.

APPENDIX A. SUPPORTING INFORMATION

Supplemental data associated with this article can be found in the online version at doi:10.1016/j.prosdent.2025.02.004.

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