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REVIEW

Synergy between artificial intelligence and precision medicine for computer-assisted oral and maxillofacial surgical planning

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Abstract

Objectives The aim of this review was to investigate the application of artificial intelligence (AI) in maxillofacial computer-assisted surgical planning (CASP) workflows with the discussion of limitations and possible future directions.

Materials and methods An in-depth search of the literature was undertaken to review articles concerned with the application of AI for segmentation, multimodal image registration, virtual surgical planning (VSP), and three-dimensional (3D) printing steps of the maxillofacial CASP workflows.

Results The existing AI models were trained to address individual steps of CASP, and no single intelligent workflow was found encompassing all steps of the planning process. Segmentation of dentomaxillofacial tissue from computed tomography (CT)/cone-beam CT imaging was the most commonly explored area which could be applicable in a clinical setting. Nevertheless, a lack of generalizability was the main issue, as the majority of models were trained with the data derived from a single device and imaging protocol which might not offer similar performance when considering other devices. In relation to registration, VSP and 3D printing, the presence of inadequate heterogeneous data limits the automatization of these tasks.

Conclusion The synergy between AI and CASP workflows has the potential to improve the planning precision and efficacy. However, there is a need for future studies with big data before the emergent technology finds application in a real clinical setting.

Clinical relevance The implementation of AI models in maxillofacial CASP workflows could minimize a surgeon's workload and increase efficiency and consistency of the planning process, meanwhile enhancing the patient-specific predictability.

Keywords Artificial intelligence · Computer-assisted surgery · Cone-beam computed tomography · Reconstructive surgical procedures

Introduction

The practice of personalized, precision, or stratified medicine is the individualization of evidence-based medicine, where a physician deviates from a traditional shotgun or one-size-fits-all approach towards devising more targeted patient-specific strategies for diagnostics, treatment planning, and preventive therapies [1]. The integration of a patient's unique clinical, demographic, imaging, and epidemiological details into the treatment planning workflow has revolutionized the healthcare industry by extending the practice of precision beyond the conventional population-based medicine. The population-based approach refers to an approach where a common treatment plan is designed having the ability to cure only a portion of the population, whereas precision medicine covers a different treatment approach for each patient by intelligently integrating patient-specific clinical, biological, and environmental data for tailored treatment planning [2, 3].

The precision approach for treatment of each individual patient is based on 4 Ps, predictive, preventive, personalized, and participatory [4]. At present, it is not possible to completely draw a picture of a patient's treatment profile due

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to the complexity of oral and maxillofacial diseases at an individual level and unpredictable nature of the outcomes. However, recent technological advancements in computer-assisted surgical planning (CASP) approaches have facilitated the advancement of precision medicine by minimizing some of the existing constraints related to one of the 4Ps, i.e., personalization, for formulating patient-specific treatment planning [5].

Three-dimensional (3D) CASP in oral and maxillofacial workflows normally encompass a combination of patient-specific planning and three-dimensional (3D) printing. Nowadays, it acts as a mainstay for the customization and delivery of personalized care in the majority of surgical workflows, such as reconstructive and orthognathic surgery, traumatology, TMJ surgery, and dental implant planning [6–11]. It allows a surgeon to three-dimensionally visualize, model, and print patient-specific solutions. CASP is mostly based on the data derived from computed tomography (CT)/cone-beam CT (CBCT) imaging. For instance, in reconstructive and orthognathic surgery, it helps to determine the osteotomy sites, positioning of bone segments, and fabrication of surgical or cutting guides and fixation plates [11].

The application of CASP has improved the clinical outcomes compared to its two-dimensional (2D) counterpart, by offering a shorter operation time, exploration of various surgical alternatives, and facilitation of a cost-effective optimized precise treatment [12–14]. However, its implementation is only limited to specialized hospitals, mainly owing to the complexity of software programs and requirement of experienced staff in both medical imaging and maxillofacial surgery [15, 16]. Furthermore, the current computational tools for CASP lack sufficient precision suffer from observer variability and are prone to extensive time consumption [16]. The key to overcoming the aforementioned limitations posed by the conventional CASP approaches could be the incorporation of artificial intelligence (AI)-based networks in the surgical workflows. In essence, AI-based on machine and deep learning algorithms have the ability to perform cognitive functions which could minimize a surgeon's workload and further enhance the practice of precision medicine in CASP [17].

Most of the efforts in oral and maxillofacial surgery have been directed towards automatizing disease diagnosis and outcome prognosis [18–20]. However, the augmentation of AI in CASP remains a topic of interest as it might become a burgeoning tool in surgical workflows for optimizing personalized treatment planning in the near future. The ultimate goal of AI-based treatment planning might be to increase efficiency and consistency of the planning process, meanwhile enhancing the patient-specific predictability. Following diagnostics, certain commonalities are shared between various maxillofacial CASP workflows, such as segmentation, multimodal image registration, virtual surgical planning (VSP), and 3D printing [21]. This review will focus on the evidence-based integration of AI in these steps of CASP for maxillofacial surgical procedures with the discussion of possible limitations and future prospects.

Segmentation

This is the first and most critical step in CASP which refers to the construction of 3D virtual models of dentomaxillofacial structures from CT/CBCT data for guiding VSP and designing patient-specific tools such as guides and implants [21]. Currently the clinical standard for segmentation is manual in nature, which is a time-consuming task requiring both anatomical and imaging expertise [22]. As time is a limiting factor in surgical workflows, fast segmentation is often required. Thereby, the alternative solution applied in these workflows is the application of semi-automatic segmentation tools which model the specific structures based on specific thresholds of Hounsfield/grayscale values [23]. Although semi-automatic processes allow quicker segmentation, they are prone to certain limitations, such as steep learning curve, need for excessive manual post-processing in the presence of high-density material artifacts, and inter-observer variability due to a manual threshold value selection which differs for each patient and anatomical region depending on the bone density [24, 25]. Furthermore, the available commercial software packages have been optimized based on CT data, which means that the accuracy of CBCT datasets segmentation is lower owing to the presence of beam hardening artifacts, inhomogeneity, and low-contrast resolution [26, 27]. Currently, CT devices are constantly being replaced with low-dose and low-cost CBCT devices for diagnosis and treatment planning in oral and maxillofacial surgery [28, 29], which could impact the quality of virtual models and precision of treatment planning without the availability of an optimal CBCT-derived segmentation software program.

Considering the limitations associated with the aforementioned traditional segmentation approaches, recent AI-based algorithms have been proposed to improve the performance of segmentation when benchmarked against manual segmentation or semi-automatic approach with manual correction as the gold standard [30, 31]. Their performances are normally assessed by either applying confusion matrix based on four variables, i.e., true positive, true negative, false positive, and false negative voxels, for the voxel-vise comparison between the AI-based segmentation and ground truth and/or by surface-to-surface volumetric superimposition matching deviation analysis for measuring the quantitative differences [32–34]. The AI algorithm's performance evaluation metrics usually involve recall, precision, accuracy, dice score, and intersection over union [33, 35]. All these metrics have been shown to provide high AI algorithm's performance with a score of over 90% for the CBCT-derived segmentation of dentomaxillofacial structures, such as mandible, alveolar bone, pharyngeal airway space, teeth, and maxillary sinus [33–37]. In addition, these AI algorithms showed no clinically or statistically significant surface deviations compared to manual segmentation. A direct comparison of AI with semi-automatic benchmark devices without manual correction has not been reported in literature due to the visible qualitative segmentation discrepancies shared by these devices due to variable patient-specific structural densities and non-CBCT standardized threshold levels for segmentation [21].

The AI-based methodologies have been successfully applied for the segmentation of CT/CBCT derived skull, maxilla, mandible, inferior alveolar nerve canal, pharyngeal airway, and teeth [33, 38–42], which could facilitate CASP in craniomaxillofacial surgical procedures. Similarly, AI-based approaches have been developed for organ-at-risk and target segmentation in head and neck oncology [43].

The computational time for generation of a 3D segmented model is one the main factors why surgeons are discouraged from switching to planning based on digital workflows. However, AI has overcome this issue by providing accurate segmentation results within a few seconds irrespective of the anatomical structures being segmented compared to the semi-automatic approaches which might take up to a few minutes to hours depending on the structure being segmented [21]. For instance, expert-based mandibular bone and full dentition segmentation in a scan takes an average of 20 min and 7 h, respectively, both of which have been reduced to less than 30 s with the application of AI-based models [35, 36]. Furthermore, the need for manual post-processing is often encountered with semi-automatic software-based approaches due to the image artifacts which significantly increase the time for CASP [21]. Even though the presence of metal artifacts drastically reduces the intensity contrast of CBCT dataset, AI has been successfully employed for robust segmentation of teeth and mandibular bone consisting of metal artifacts with high-performance values [44, 45]. These state-of-the-art AI based networks have the ability to discriminate anatomy from metal artifacts and could offer a unique possibility of improving the CASP workflows by the elimination of inaccuracies and time constraints posed in patients with artifacts [44]. Nevertheless, future research needs to be conducted to further improve the existing AI algorithms, integrate other anatomical structures, and address challenging cases with both motion and metal artifacts [46].

Another important aspect of segmentation is the observer dependency, where the final segmented structure might vary depending on the observer's experience and repeatability. Recently applied AI approaches for medical image segmentation are deterministic in nature with a predefined set of mathematical operations, which allows a network to produce an identical segmented structure from the same image, hence, offering 100% consistency without any inter- and intra-observer variability [41, 47].

Generally, the computational power of the personal computers in a clinical setting is not enough for running the AI-based networks, which requires high-performance computers. To overcome this problem, the technological advancements have allowed deployment and integration of the AI models onto online cloud-based platforms, which lets a surgeon automatically segment the required dentomaxillofacial structures for planning without the need for an experienced observer or a high-performance computer [40]. Figure 1 illustrates an example of a cloud-based platform for the automatic segmentation of dentomaxillofacial structures.

Clinically, the production of accurate surface-rendered models through AI algorithms could be beneficial for several oral and maxillofacial procedures, especially within the fields of dental implantology, tooth autotransplantation, orthognathic surgery, and navigational surgeries, where precision is of paramount importance. However, the main barriers inhibiting the wide adoption of AI for segmentation in a clinical practice include data variability due to different scanning devices, acquisition parametrization, and image quality inconsistency with respect to contrast, resolution, and signal-to-noise, which lead to poor generalizability of the available algorithms. This generalization gap can be bridged by training of the AI algorithms based on a large variety of datasets generated from multi-center initiatives for improving the clinical workflows [21].

Multimodal image registration

Registration or fusion is the process of mapping two or more coordinate systems. In medical imaging, it refers to the superimposition of 3D images acquired from different imaging modalities into the same coordinate frame based on certain matching criteria [48]. Any misalignment would impact the CASP based on the digital model. It is performed to utilize the strengths and complement the weaknesses of different imaging modalities [49]. For instance, integration of MRI with CT imaging in oral oncology provides intricate details of both osseous and soft tissue and tumor characteristics during planning [50].

The commonly applied registration methods are either extrinsic or intrinsic in nature. Extrinsic registration is performed by matching invasive foreign objects which are fixed onto the patient during different image acquisitions, such as fiducial markers, miniscrews, and occlusal splints. Intrinsic approaches are marker-free, where similar features of different scans are extracted based on either anatomical or

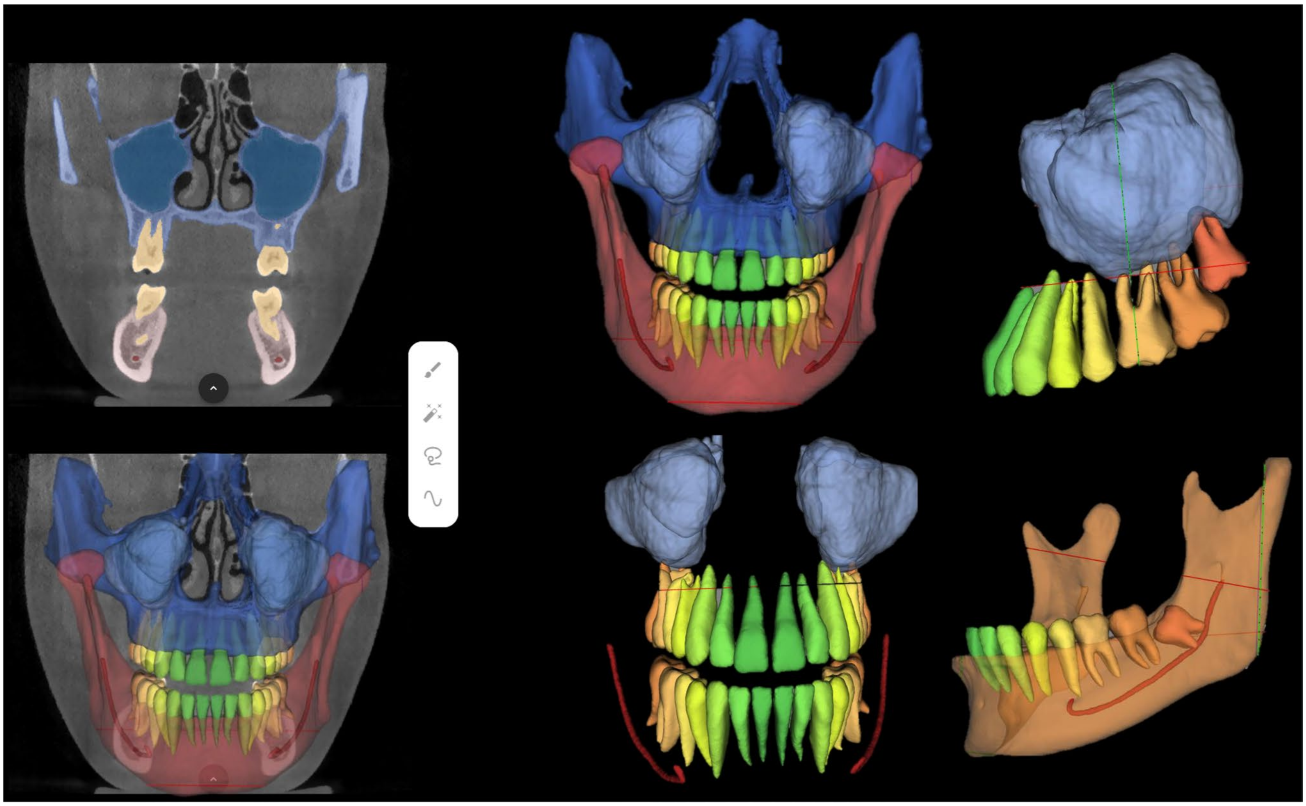

Fig. 1 Automatic labelling, identification, and segmentation of cone-beam computed tomography-derived maxillofacial skeleton, teeth, maxillary sinus, and inferior alveolar nerve canal (Relu BV, Leuven, Belgium)

mathematical landmarks, surfaces, and voxels, which are then matched to conduct the coordinate alignment [49]. Several open-source and commercial software tools are available in the market for performing craniomaxillofacial image registration. Their main limitations are excessive time consumption, lack of robustness depending on the extent of metal artifacts, and requirement of well-skilled medical engineers [21, 51]. Furthermore, none of the programs have been integrated with AI-based solutions for improving the efficacy of the registration process.

Multimodal image registration lies at the realm of various CASP pathways in oral and maxillofacial surgery for the creation of a virtual patient, such as CBCT/intraoral scanner/3D photography in orthognathic surgery, dental implant planning, cleft lip and palate, and reconstructive surgery; positron emission tomography (PET)/MRI/CT for CASP in maxillomandibular reconstructive surgery; and SPECT (single photon emission computed tomography)/CT for surgical and radiation therapy planning of oral and maxillofacial tumors [49, 51–56].

For an accurate depiction of dentition, CBCT combined with complimentary dental imaging by intraoral scanners is a necessity to negate the impact of distorted occlusal area by scattering caused by metal artifacts on CBCT images. Clinically, this type of multimodal imaging is vital during planning for maxillofacial surgical procedures, where occlusal-surface-supported devices such as drilling, saw, and repositioning guides are required [55]. Recent advent in AI has allowed fully automated registration of CBCT/optically scanned dental models with a comparable accuracy to manual landmark-based registration for possible application in orthognathic surgery and dental implant planning [56]. Chung et al. [56] investigated the performance of an automated AI-based registration by comparing with a manual three-point-based registration provided by experts as a ground truth. The accuracy was assessed by measuring the Euclidean distance errors of the landmarks, which showed no significant variance from the ground truth, and the landmark distance error was less than 2 mm. The proposed method also outperformed other existing registration algorithms commonly incorporated in the software devices by reducing the distance error by approximately 30 to 70%. This approach might solve the limitations posed by the traditional approach, such as labor intensiveness and observer variability [21]. However, as point-based registration relies on ICP method, where closest point pair is used as a matching area to register and in cases where CBCT is contaminated with metal artifacts, an accurate superimposition is prevented due to the presence of many non-congruent points [57]. One possible solution in such cases could be a combination of AI-based segmentation and registration. Jang et al.

[51] trained an AI segmentation algorithm based on panoramic images derived from CBCT scans which significantly overcame the impact of metal artifacts. Following automatic segmentation of teeth, the AI model automatically generated global-to-local tooth registration between CBCT and optical scan. The automated approach was compared with manual initial registration which showed that both landmark and surface deviations of the automated registration were found to be within the range of 0.5 mm, whereas the manual approach showed deviation values of more than 1 mm. The inclusion of such AI-based algorithms in a daily practice could replace the traditional point-based method which might be able to offer comparable or improved accuracy, robustness, and time efficiency without the need of additional manual input for the purpose of designing surgical wafers in orthognathic surgery and dental implant planning [21].

Li et al. [58] proposed an end-to-end landmark-guided rigid registration network to register MRI/CBCT of the TMJ with large field of view differences, which not only solved the issue of FOV difference but also provided a time-efficient and accurate alternative to other manual and semi-automatic approaches. When compared with the manual ground truth, the automated approach showed a high performance with mutual information and structural similarity values of 0.57 ± 0.07 mm and 0.06 ± 0.02 mm, respectively. In addition, the time required for registration was 0.016 s, whereas the manual method took > 2.0 h. This multimodal registration could provide additional information to a surgeon while CASP of TMJ surgeries with an accurate visualization of the articular disc and condyle surfaces.

Although AI algorithms have been proposed to overcome the taxing manual labor by automatizing the manual tasks associated with traditional multimodal registration techniques, it is relatively in its infancy stage. The majority of work for the creation of a virtual patient has been based on automatizing registration between the CT/CBCT images and the optically scanned dental models [51, 56], whereas lack of evidence exists related to other types of image registrations. At the same instance, these AI algorithms are yet to be deployed for CASP workflows in maxillofacial surgery.

Virtual surgical planning

The next step in CASP is known as VSP, which is usually performed using commercial surgical planning software packages [59]. The reconstructed and registered digital patient models are manipulated for various tasks, such as determination of optimal cutting planes for osteotomies, positioning of bony segments, exploration of different operative approaches, and soft tissue simulation. Thereafter, the programs allow designing of patient-specific surgical wafers, cutting and positioning guides, prebent plates, and implants [16].

Although VSP for maxillofacial procedures has been employed for more than 35 years with indisputable advantages over traditional 2D planning [60], its implementation is still limited to specialized hospitals mainly owing to the complexity of software programs requiring well-trained technicians and steep learning curve [15]. Additionally, the contested inaccuracy of VSP versus actual surgical outcome in orthognathic and plastic and reconstructive surgery has also been well documented which can negatively impact the precision of treatment delivery [8, 61]. Accuracy is an important aspect of VSP as it determines the success of a surgical procedure and patient satisfaction.

Until now, both AI-based machine and deep learning frameworks have mainly been employed for improving the accuracy of virtual soft-tissue simulation in the VSP pathway of orthognathic surgery [16, 62]. These algorithms have been trained with 3D face scans of healthy volunteers and orthognathic surgery patients, which allows automatic simulation of the required postoperative change in facial soft tissue. Hence, the planning step is reduced to only a single step, i.e., the necessary amount and direction of bone movement to achieve the simulated soft tissue position. Knoops et al. [16] reported that their machine learning framework was able to diagnose orthognathic shape features with 95.5% sensitivity and 95.2% specificity. In addition, their automated postoperative face shape simulation compared to the ground-truth postoperative shape was able to offer a mean accuracy of 1.1 ± 0.3 mm, which is comparable to the traditional software packages offering simulation accuracy within the range of 0.5 to 2 mm. In another study, Horst et al. [62] developed an AI-based method for simulating soft-tissue profiles following mandibular advancement surgery. They generated the soft tissue simulations with AI and also with Mass Tensor Model (MTM) algorithm, which is one of the most commonly employed and accurate algorithms in surgical planning software programs. Later, both simulations were compared with the actual postoperative soft tissue profile. The findings suggested that the AI approach provided with a significantly lower error (1.0 ± 0.6 mm) compared to the MTM-based simulation (1.5 ± 0.5 mm), hence, confirming the clinical applicability of these AI approaches which could further facilitate in making the surgical planning more precise, objective, and cost-effective.

In reconstructive and cleft lip and/or palate surgery [63, 64], AI-based recognition of the facial skeleton midplane has been proposed which is a vital step for pre-surgical planning of deformed or traumatized tissue and implant design techniques. Although optimal performance has been reported for obtaining a midplane of symmetric skull with a DSC score of around 99% compared to manual ground truth labels, there is still a need to improve its performance for deformed or asymmetric images before it can be utilized for clinical applications [64]. In head and neck oncology, AI algorithms have been developed for intensity modulated radiotherapy (IMRT) and adaptive radiotherapy planning within the VSP chain to reduce the clinical strain and improve the dosimetric integrity [43, 65], which is normally a labor-intensive and time-consuming process requiring many iterations between experienced oncologists and dosimetrist. However, these solutions are still at their early developmental stage, and an improvement in their performance is necessary before widespread deployment.

In dental implant planning, AI-based algorithms have been mainly applied for guiding the decision-making process for formulating a plan on the need for implant placement with/without bone graft, type and design of prosthesis (fixed or removable), implant abutment selection, and selection of the optimum implant length and design [66–69]. However, only a few studies have focused towards the VSP aspect, where these algorithms have been proposed for automatically calculating bone dimensions and localizing the position of prospective dental implant placement sites on CBCT images [70, 71]. The performance of these algorithms is still below par compared to the manual ground truth, and further refinements are required before their implementation in a clinical practice.

Generally, the training and accuracy of AI-based networks rely on big data, which also holds true for VSP [21]. Even though recent development of automated AI tools for VSP in orthognathic surgery has the tendency to improve the clinical decision-making process to a certain level, there is still room for improvement. Future studies are required for a potential integration of dental, skeletal, and soft tissue into a single model using a large patient cohort and inclusion of diverse maxillofacial surgical procedures. Furthermore, the combination of these virtual models with electronic medical records might possibly pave the way towards a new horizon of precision medicine.

3D manufacturing

The final step in CASP workflow is the translation of a specific virtual design to a physical product by 3D printing. It involves three major steps: (a) modeling, generation of virtual blueprints of a model to be printed with computer-aided designing (CAD); (b) printing, physical fabrication of the model with layered deposition of a material; and (c) finishing, post-processing, and cleaning to achieve the final model [72]. 3D printing is often required for CASP where patient-specific tools are needed during a procedure, such as surgical wafers, cutting and positioning guides, prosthesis, implants, and anatomical models for adjustment of plates or titanium mesh [73]. Traditionally, the designing is performed using either commercial software packages which are financially expensive and license driven or open-source programs whose application is limited due to lack of CE certification for medical applications. Furthermore, other key issues pertain to the availability of experts for modeling, cost, and manufacturing time [74].

In that context, AI has already laid a foundation towards automatization of the printing process in craniomaxillofacial surgery by converting traditional 3D printing to intelligent manufacturing. For instance, AI-based platforms have already been proposed to automatically design patient-specific cranial implants for skull defect repair following cranioplasty [74, 75]. This might solve the issue of automatically producing 3D printable and directly implantable shapes. Additionally, AI-based algorithms have also been proposed for reproducing the color of maxillofacial prostheses to that of natural skin by automatic selection of required pigments volume, which has the ability to overcome the expensive and non-efficient color-matching systems for prosthesis fabrication in cases of maxillofacial defects [76]. At the same instance, application of intelligent manufacturing in other fields of maxillofacial surgery is limited.

Although AI has been proposed for in vitro optimization of the printing parameters [77], the incorporation of these algorithms in the field of surgery still needs to be investigated for automatic optimal selection of material and technical parameters for printing patient-specific tools. So far, AI has stepped in the designing and printing steps of the workflow; however, post-processing still requires human intervention. Therefore, at present it is impossible to use AI for controlling the complete 3D printing process.

Conclusions and future perspectives

The integration of AI in oral and maxillofacial surgery has shown great potential for screening, diagnostics, and treatment outcome prediction. However, when considering precision of treatment planning, the synergy between AI and CASP workflows is still below par. It is worth noting that the augmentation of AI in the healthcare industry has been booming for the past few years; however, the level of evidence for treatment planning in oral and maxillofacial surgery is still limited. Most of the AI algorithms have been trained to address individual steps of CASP, and no single intelligent workflow exists encompassing all aspects of the planning workflow. Segmentation of dentomaxillofacial tissue has been the most explored area which has been considered satisfactory for clinical use. Nevertheless, a lack of generalizability is the main issue posed by these algorithms, as the majority of models have been trained with the data derived from a single device and imaging protocol which might not offer similar performance when considering other devices. In relation to the later steps of CASP, such as registration, VSP, and 3D printing, a lack of adequate heterogeneous data limits the integration of AI for automatizing these tasks to be used in a clinical practice. Table 1 summarizes the general limitations associated with conventional CASP and possible advantages of integrating AI into the workflows. Furthermore, certain future recommendations are proposed below to improve the possible direction of AI for future research:

- Big data is one of the fundamental obstacles for the integration of AI models in oral and maxillofacial CASP. Efforts should be made to employ big data provision by developing cloud-based databases acquired from multiple centers with different settings and level of artifacts to improve the generalizability of models, with the ultimate goal of improving the precision of planning in patients with rare and complicated diseases.
- Demonstration of the safety and efficacy of the AI models for ensuring that all required regulatory conditions are sufficiently met. At present, models lack standardization, CE certification, and medical device regulation (MDR) compliance. Furthermore, cost–benefit ratio and cost-effectiveness of AI needs to be established.
- Requirement of comparative studies assessing the accuracy of integrated 3D models to ensure high performance of the AI algorithms compared to the status quo benchmark software programs.
- At present, the majority of studies exemplify their models' performance based on private datasets which is inconvenient for benchmarking if future growth is to be expected. A possible solution could be deployment of the AI models in the form of commercial or open-source software packages for benchmarking their performance against other models and validating their clinical applicability. In addition, it is also important to benchmark the performance of different AI algorithms for similar tasks.
- AI-based multimodal image registration especially CBCT/IOS/facial scanning for the creation of a virtual patient is a novel area for research with limited available evidence and has plenty of clinical implications in the workflows of plastic, reconstructive and orthognathic surgery, dental implant planning, and traumatology, which needs to be further explored on the road for achieving an AI virtual model. For future AI-based registration studies, it is important to address the issues of ground-truth data generation and to define a clear similarity criterion between two or more imaging modalities for optimal registration. Furthermore, it is also crucial to test the robustness of these algorithms in the presence of metal artifacts which is still considered a challenging task for automatizing the image matching process.
- Automatization of the 3D printing process should focus towards devising methods for auto-designing of patient-specific wafers, cutting and positioning guides, and implants. This could be achieved by incorporating AI-based algorithms which have the ability to learn the shape deviations from past printing jobs. At the same instance, printing parameters should be automatized such as material selection, layer resolution, and design

Table 1 General limitations of conventional computer-assisted surgical planning (CASP) and possible advantages of integrating of artificial intelligence (AI)-based networks into the workflows

	Conventional CASP limitations	Possible advantages of AI integration
Segmentation	– Observer variability and labor intensiveness – Steep learning curve – Need for manual post-processing – Lacks robustness in the presence of artifacts – Requires computers with high computational power	– Time-efficiency – Observer and experience independence – Improved performance against artifacts – No need for post-processing – Deploying onto cloud-based platforms overcomes the need for high-performance computer
Multimodal image registration	– Lacks robustness in the presence of artifacts – Labor intensiveness	– Automatic registration without the need for manual input – Exclusion of artifacts from surfaces being registered
Virtual surgical planning	– Observer variability and labor intensiveness – Reduced accuracy compared to actual surgical outcome	– Automatic determination of optimal cutting planes for osteotomies, placement of surgical guides and implants, positioning of bony segments, and treatment simulation
Three-dimensional manufacturing	– High modeling cost and manufacturing time – Requirement of a modeling expert – Manual selection of printing parameters – Manual post-processing	– AI-based modeling by training algorithm from past printing jobs – Automatic selection of the printing parameters based on object to be printed – Robotic post-processing to remove the possibility of human error

orientation depending on the structure being printed, for overcoming the steep learning curve which could ensure universal applicability of 3D printers without the requirement of a trained professional.

Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest The authors declare no competing interests.

Informed consent For this type of study, formal consent is not required.

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