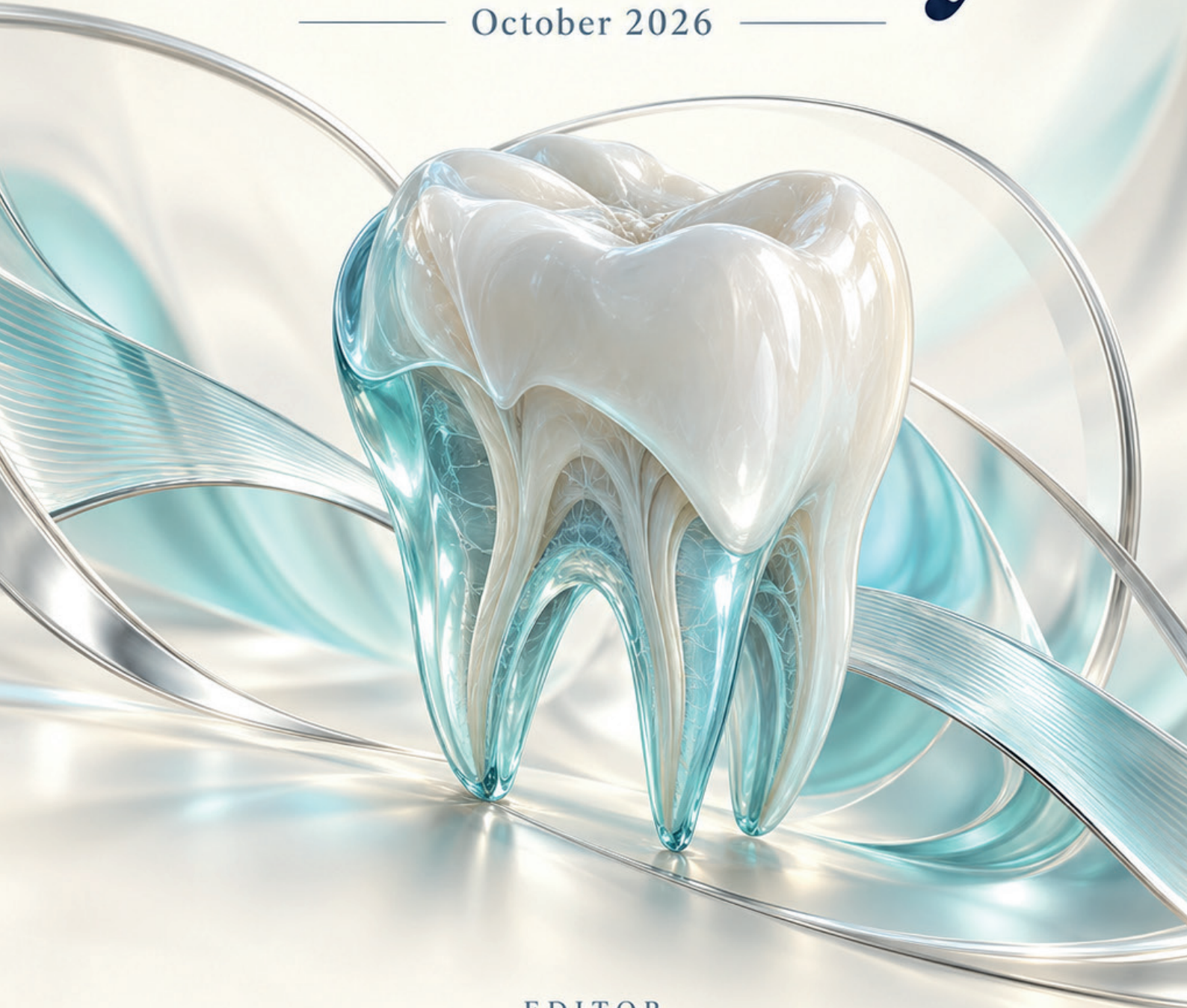


International Studies in the field of **Dentistry**

October 2026



EDITOR

Prof. Dr. Emin Caner TÜMER

gece
kitaplığı

İmtiyaz Sahibi / Yaşar Hız
Yayına Hazırlayan / Gece Kitaplığı

Birinci Basım / Ekim 2026 - Ankara
ISBN / 978-625-321-294-0

© copyright

Bu kitabın tüm yayın hakları Gece Kitaplığı'na aittir.
Kaynak gösterilmeden alıntı yapılamaz, izin almadan hiçbir yolla çoğaltılamaz.

Gece Kitaplığı

Kızılay Mah. Fevzi Çakmak 1. Sokak
Ümit Apt No: 22/A Çankaya/ANKARA
0312 384 80 40
www.gecekitapligi.com / gecekitapligi@gmail.com

Baskı & Cilt

Bizim Büro
Sertifika No: 42488

**INTERNATIONAL STUDIES
IN THE FIELD OF
DENTISTRY**

October 2026

EDITOR

Prof. Dr. Emin Caner TÜMER

CONTENTS

CHAPTER 1

ORAL SURGERY IN THE ELDERLY PATIENT: CHALLENGES AND CLINICAL CONSIDERATIONS

Özge ÖZDAL ZİNCİR 7

CHAPTER 2

TRAUMATIC DENTAL INJURIES IN THE PRIMARY DENTITION

Sıla Beren ADIGÜZEL ERDOĞAN 27

CHAPTER 3

MACHINE LEARNING AND PREDICTIVE ANALYTICS IN IMPLANT DENTISTRY

Özge ÖZDAL ZİNCİR 39

CHAPTER 4

DIGITAL FABRICATION OF PROVISIONAL RESTORATIONS IN FIXED PROSTHODONTICS: MATERIALS, TECHNOLOGIES, AND CLINICAL DECISION-MAKING

Beşar İZZETAĞA , Duygu Ece KESKİN 61

CHAPTER 5

POTENTIAL RISKS AND CHALLENGES OF ARTIFICIAL INTELLIGENCE IN DENTISTRY: SPECIAL EMPHASIS ON DENTOMAXILLOFACIAL RADIOLOGY

Merve YÜCE, Birdal AYKUT, Birsay GÜMRÜ 82

CHAPTER 1

ORAL SURGERY IN THE ELDERLY PATIENT: CHALLENGES AND CLINICAL CONSIDERATIONS

Özge ÖZDAL ZİNCİR¹

¹ Assoc. Prof. Dr. Istanbul University- Cerrahpasa Faculty of Dentistry, Department of Oral and Maxillofacial Surgery ORCID: 0009-0000-9423-5764

Introduction

The global population is aging rapidly, and the proportion of elderly individuals requiring oral healthcare continues to increase significantly. Improvements in medical care, nutrition, and socioeconomic conditions have contributed to longer life expectancy, resulting in a growing number of older adults retaining their natural dentition and seeking advanced dental and surgical treatments [1].

Oral and maxillofacial surgeons increasingly encounter geriatric patients presenting with complex medical histories, multiple medications, functional limitations, and age-related physiological changes that substantially influence diagnosis, treatment planning, surgical management, and postoperative healing [2].

Aging is associated with progressive alterations in systemic physiology affecting cardiovascular, respiratory, renal, hepatic, endocrine, immune, and musculoskeletal systems [3]. These changes may impair tissue healing, increase surgical risk, alter pharmacological responses, and complicate perioperative management.

Polypharmacy is particularly common among elderly individuals because of high prevalence of chronic diseases such as hypertension, diabetes mellitus, cardiovascular disease, osteoporosis, neurodegenerative disorders, and malignancy [4]. Drug interactions, anticoagulant therapy, bisphosphonate use, xerostomia-inducing medications, and immunosuppressive agents are therefore frequent considerations in oral surgery.

Another important issue involves frailty, a multidimensional syndrome characterized by reduced physiological reserve and increased vulnerability to stressors [5]. Frail elderly patients may demonstrate poorer surgical tolerance, prolonged recovery, and increased postoperative complications.

Oral health problems are highly prevalent in geriatric populations and include edentulism, root caries, periodontal disease, mucosal lesions, xerostomia, oral cancer, temporomandibular disorders, osteonecrosis, and prosthetic complications [6].

The elderly population additionally demonstrates increasing demand for implant rehabilitation, reconstructive procedures, and advanced oral surgical interventions [7]. Careful risk-benefit analysis is therefore essential when planning treatment.

Management of elderly surgical patients requires individualized evaluation integrating systemic health status, cognitive function, nutritional condition, functional independence, social support, and quality-of-life considerations [8].

Minimally invasive surgical approaches, careful pharmacological management, interdisciplinary collaboration, and comprehensive postoperative care are especially important in geriatric patients [9].

This chapter reviews the physiological aspects of aging, systemic diseases, pharmacological considerations, oral surgical procedures, implant therapy, infection management, medication-related complications, anesthesia considerations, frailty assessment, postoperative care, and future perspectives regarding oral surgery in elderly patients.

Physiological Changes Associated with Aging

Aging produces progressive anatomical and physiological alterations that significantly influence oral surgical management and healing capacity [10].

Cardiovascular System

Age-related cardiovascular changes include reduced vascular elasticity, increased arterial stiffness, decreased cardiac reserve, and impaired autonomic regulation [11].

These alterations may reduce tolerance to surgical stress, anesthesia, fluid shifts, and blood loss. Hypertension, coronary artery disease, arrhythmias, and heart failure are therefore common perioperative concerns in elderly patients [12].

Respiratory System

Pulmonary aging is associated with reduced lung elasticity, diminished respiratory muscle strength, decreased vital capacity, and impaired mucociliary clearance [13].

These changes increase susceptibility to hypoxia, aspiration, postoperative pulmonary complications, and sedation-related respiratory depression [14].

Renal and Hepatic Function

Renal perfusion and glomerular filtration rate gradually decline with aging, altering elimination of many medications commonly used in oral surgery [15].

Hepatic metabolism may additionally decrease, prolonging drug half-life and increasing risk of toxicity [16].

Careful dose adjustment of analgesics, sedatives, and antibiotics is therefore essential in elderly patients.

Immune System

Immunosenescence refers to age-related decline in immune function associated with impaired inflammatory response, delayed wound healing, and increased infection susceptibility [17].

Reduced immune competence may contribute to prolonged postoperative recovery and increased risk of osteomyelitis or surgical site infection.

Bone Metabolism

Aging additionally affects bone remodeling and mineral density. Osteoporosis and reduced osteoblastic activity may impair bone healing and increase fracture risk [18].

These changes are particularly relevant in implant surgery, extractions, and maxillofacial trauma management.

Understanding age-related physiological changes is essential for safe surgical planning and perioperative management in geriatric patients.

Comprehensive Geriatric Assessment in Oral Surgery

Chronological age alone is often an inadequate predictor of surgical risk because elderly individuals demonstrate substantial variability in functional and systemic health status [19].

Comprehensive geriatric assessment is therefore increasingly important in treatment planning and risk stratification.

Medical Evaluation

Detailed medical history should include cardiovascular disease, diabetes mellitus, osteoporosis, chronic kidney disease, pulmonary disease, neurologic disorders, malignancy, and previous surgeries [20].

Assessment of functional capacity and exercise tolerance may additionally provide important information regarding perioperative risk.

Medication Review

Polypharmacy is highly prevalent among elderly patients and significantly influences oral surgical management [21].

Common medications of concern include; anticoagulants, antiplatelet agents, bisphosphonates, corticosteroids, antihypertensives, psychotropic medications, immunosuppressants [22].

Potential drug interactions and adverse reactions must be carefully evaluated before surgery.

Cognitive and Psychological Assessment

Cognitive impairment, dementia, depression, anxiety, and delirium may affect informed consent, treatment compliance, postoperative care, and pain perception [23].

Communication strategies should therefore be adapted appropriately.

Nutritional Status

Malnutrition and sarcopenia are common in elderly populations and may impair wound healing and immune function [24].

Nutritional screening may help identify high-risk patients requiring dietary support.

Frailty Assessment

Frailty is increasingly recognized as an important predictor of surgical outcomes [25].

Frail patients demonstrate increased risk of postoperative complications, hospitalization, functional decline, and mortality.

Comprehensive assessment allows individualized treatment planning and optimization of perioperative care.

Pharmacological Considerations and Polypharmacy

Polypharmacy is one of the most important challenges in geriatric oral surgery because elderly patients frequently use multiple medications simultaneously [26].

Drug interactions, altered pharmacokinetics, reduced organ function, and increased sensitivity to medications significantly influence perioperative management [27].

Anticoagulants and Antiplatelet Agents

Direct oral anticoagulants, warfarin, aspirin, and clopidogrel are increasingly common among elderly patients because of cardiovascular disease prevalence [28].

Risk of postoperative bleeding must be balanced against thromboembolic risk associated with medication discontinuation [29].

Current evidence generally supports continuation of many anticoagulants for minor oral surgical procedures combined with appropriate local hemostatic measures [30].

Bisphosphonates and Antiresorptive Drugs

Bisphosphonates and denosumab are widely prescribed for osteoporosis and metastatic bone disease [31].

These medications are associated with risk of medication-related osteonecrosis of the jaw (MRONJ), particularly following extractions or invasive surgery [32].

Risk assessment and preventive strategies are therefore essential in elderly patients receiving antiresorptive therapy.

Analgesics and Sedatives

Elderly patients demonstrate increased sensitivity to opioids, benzodiazepines, and sedative agents because of altered metabolism and reduced physiological reserve [33].

Nonsteroidal anti-inflammatory drugs may additionally increase risk of renal dysfunction, gastrointestinal bleeding, and cardiovascular complications [34].

Multimodal pain management and cautious dosing strategies are therefore recommended.

Antibiotics

Renal and hepatic function should be considered when prescribing antibiotics in geriatric populations [35].

Overprescription may additionally increase risk of *Clostridioides difficile* infection and antimicrobial resistance.

Careful pharmacological management significantly reduces perioperative complications in elderly oral surgery patients.

Tooth Extractions in Elderly Patients

Tooth extraction remains one of the most common oral surgical procedures performed in elderly populations [36].

However, extractions in geriatric patients may become more complex because of ankylosis, hypercementosis, osteoporosis, reduced bone elasticity, limited mouth opening, and medication-related risks [37].

Fragile mucosa and reduced vascularity may additionally impair soft tissue healing.

Patients receiving anticoagulants or antiplatelet therapy require careful hemostatic planning [38].

Local hemostatic measures including sutures, oxidized cellulose, collagen sponges, fibrin sealants, and tranexamic acid mouth rinses may significantly reduce postoperative bleeding risk [39].

Atraumatic extraction techniques are especially important in elderly individuals because excessive trauma may increase risk of delayed healing, fracture, or osteonecrosis [40].

Postoperative monitoring should additionally consider nutritional status, cognitive function, pain control, and oral hygiene capability.

Dental Implant Surgery in Elderly Patients

Increasing numbers of elderly individuals seek implant-supported rehabilitation because of improved expectations regarding oral function and quality of life [41].

Chronological age alone is not considered a contraindication for implant therapy, and numerous studies have demonstrated favorable implant survival rates in older adults [42].

However, systemic health, bone quality, medication use, dexterity, cognitive status, and oral hygiene capacity must be carefully evaluated [43].

Osteoporosis and reduced bone density may influence implant stability and osseointegration, although evidence regarding implant survival in osteoporotic patients remains generally favorable [44].

Minimally invasive implant protocols, guided surgery, flapless techniques, and shortened treatment times may reduce morbidity in geriatric patients [45].

Careful prosthetic planning is additionally important because manual dexterity limitations may affect hygiene maintenance around implant-supported restorations [46].

Implant therapy may significantly improve mastication, nutrition, speech, and psychosocial well-being in appropriately selected elderly patients [47].

Medication-Related Osteonecrosis of the Jaw in Elderly Patients

Medication-related osteonecrosis of the jaw represents one of the most important oral surgical complications encountered in elderly populations because antiresorptive and antiangiogenic medications are commonly prescribed in this age group [48].

Bisphosphonates and denosumab are widely used for osteoporosis, metastatic bone disease, multiple myeloma, and other skeletal conditions [49].

MRONJ is characterized by exposed necrotic bone or persistent intraoral fistula in patients with current or previous antiresorptive therapy and no history of radiation therapy to the jaws [50].

Elderly patients are particularly susceptible because of increased prevalence of systemic disease, reduced healing capacity, poor oral hygiene, and cumulative medication exposure [51].

Tooth extractions, dentoalveolar surgery, periodontal disease, and poorly fitting prostheses are common triggering factors [52].

Preventive dental evaluation before initiation of antiresorptive therapy is therefore strongly recommended [53].

When invasive surgery becomes necessary, minimally traumatic techniques, primary closure, antibiotic prophylaxis, and careful postoperative monitoring may reduce risk [54].

Management strategies for MRONJ include conservative treatment, antimicrobial therapy, surgical debridement, resection, platelet concentrates, laser therapy, and regenerative adjuncts depending on disease severity [55].

Early diagnosis and interdisciplinary collaboration among oral surgeons, physicians, oncologists, and endocrinologists remain essential for successful management.

Oral Cancer and Precancerous Lesions in Elderly Patients

The incidence of oral squamous cell carcinoma increases significantly with age, making elderly patients a major risk group for oral malignancies [56].

Chronic tobacco use, alcohol consumption, nutritional deficiencies, immunosenescence, and cumulative carcinogenic exposure contribute to increased cancer prevalence in geriatric populations [57].

Common clinical presentations include persistent ulcers, leukoplakia, erythroplakia, exophytic masses, induration, dysphagia, and unexplained pain [58].

Delayed diagnosis is unfortunately common in elderly individuals because lesions may initially be asymptomatic or overlooked [59].

Biopsy procedures in elderly patients require careful medical evaluation, particularly in anticoagulated or medically compromised individuals [60].

Treatment planning for oral cancer must balance oncologic control with quality-of-life considerations, functional preservation, nutritional status, and systemic tolerance to surgery or adjuvant therapy [61].

Frailty assessment and multidisciplinary oncologic management are particularly important in elderly head and neck cancer patients [62].

Early detection and regular oral examination remain critical for improving prognosis and reducing morbidity.

Maxillofacial Trauma in the Elderly

Maxillofacial trauma in elderly individuals differs substantially from trauma patterns observed in younger populations [63].

Falls represent the most common etiology because of impaired balance, visual deficits, sarcopenia, neurologic disease, and polypharmacy-related dizziness [64].

Elderly trauma patients frequently present with systemic comorbidities, osteoporosis, anticoagulant therapy, and reduced physiological reserve, all of which complicate management [65].

Mandibular fractures in elderly edentulous patients may demonstrate delayed healing because of reduced vascularity and diminished bone volume [66].

Conservative management may occasionally be preferred in frail patients unable to tolerate extensive surgery [67].

However, prolonged immobilization should generally be avoided because it may increase risk of malnutrition, pulmonary complications, and functional decline [68].

Rigid fixation techniques and minimally invasive surgical approaches may facilitate earlier mobilization and improved postoperative recovery [69].

Careful perioperative medical optimization and interdisciplinary collaboration are especially important in geriatric trauma management.

Anesthesia and Sedation Considerations

Anesthesia management in elderly oral surgery patients requires special attention because aging significantly alters physiological response to sedatives, anesthetics, and surgical stress [70].

Reduced cardiovascular reserve, impaired pulmonary function, altered hepatic metabolism, and decreased renal clearance increase susceptibility to perioperative complications [71].

Local anesthesia remains the safest approach whenever feasible because it minimizes systemic risk [72].

However, vasoconstrictor use should be carefully considered in patients with severe cardiovascular disease or uncontrolled hypertension [73].

Conscious sedation may improve patient comfort and cooperation but requires cautious dosing because elderly patients are highly sensitive to benzodiazepines and opioids [74].

General anesthesia may be indicated for extensive procedures, severe anxiety, cognitive impairment, or complex reconstruction; however, postoperative delirium, respiratory complications, and prolonged recovery are more common in elderly individuals [75].

Preoperative medical consultation and careful anesthesia planning significantly improve patient safety.

Postoperative Care and Complications

Postoperative management is critically important in elderly surgical patients because complications may develop more rapidly and recovery is often prolonged [76].

Pain control should balance adequate analgesia with avoidance of excessive sedation, respiratory depression, constipation, or delirium [77].

Nutritional support is especially important because elderly individuals frequently demonstrate reduced appetite, swallowing difficulty, or preexisting malnutrition [78].

Hydration status should additionally be monitored carefully because dehydration may contribute to confusion, renal dysfunction, and delayed healing [79].

Common postoperative complications in geriatric oral surgery patients include; delayed wound healing, infection, bleeding, dry socket, delirium, aspiration, medication interactions, functional decline [80].

Caregiver involvement and clear postoperative instructions are often essential because cognitive or sensory impairment may affect compliance [81].

Frequent follow-up and early complication management significantly improve outcomes in elderly patients.

Ethical and Quality-of-Life Considerations

Ethical decision-making plays a particularly important role in geriatric oral surgery because treatment goals may differ substantially among elderly individuals [82].

Chronological age alone should not determine treatment eligibility; however, patient autonomy, frailty, systemic disease burden, cognitive status, life expectancy, and quality-of-life expectations must all be considered [83].

Shared decision-making involving patients, caregivers, physicians, and oral surgeons is especially important when planning invasive or extensive surgical procedures [84].

Functional outcomes such as nutrition, speech, pain reduction, social interaction, and independence are often more important than purely anatomical reconstruction in elderly populations [85].

Palliative approaches may occasionally be more appropriate than aggressive surgical intervention in medically fragile patients [86].

Ethically balanced individualized treatment planning therefore remains fundamental in geriatric oral surgery.

Future Perspectives

The growing elderly population is expected to substantially increase demand for geriatric oral surgical care in coming decades [87].

Minimally invasive surgical techniques, digital workflows, guided implant surgery, regenerative medicine, and artificial intelligence-assisted treatment planning are likely to improve safety and predictability in elderly patients [88].

Frailty assessment tools and personalized risk stratification models may further optimize perioperative decision-making [89].

Regenerative approaches including platelet concentrates, stem-cell-based therapies, and biologically active biomaterials may improve healing in aging tissues [90].

Telemedicine and remote monitoring systems may additionally facilitate postoperative follow-up and improve access to care for elderly individuals with mobility limitations [91].

Interdisciplinary collaboration among oral surgeons, geriatricians, anesthesiologists, oncologists, prosthodontists, and primary care physicians will become increasingly important [92].

Future oral surgical care is therefore expected to move toward more personalized, multidisciplinary, minimally invasive, and quality-of-life-centered approaches for geriatric patients.

Conclusion

The elderly population represents one of the fastest-growing patient groups in oral and maxillofacial surgery. Aging-associated physiological changes, systemic diseases, polypharmacy, frailty, and altered healing capacity significantly influence diagnosis, treatment planning, surgical management, and postoperative care.

Successful oral surgery in geriatric patients requires comprehensive individualized evaluation extending beyond chronological age alone. Medical assessment, medication review, cognitive function, nutritional status, frailty, and quality-of-life considerations are all essential components of treatment planning.

Tooth extractions, implant therapy, trauma management, oral cancer surgery, and treatment of medication-related osteonecrosis may all be safely performed in elderly individuals when appropriate precautions and minimally traumatic approaches are used.

Careful pharmacological management, interdisciplinary collaboration, atraumatic surgical technique, optimized anesthesia protocols, and comprehensive postoperative monitoring significantly reduce morbidity and improve outcomes.

Future advances in digital surgery, regenerative medicine, minimally invasive techniques, and personalized geriatric care are expected to further improve safety and functional rehabilitation in elderly oral surgery patients.

Overall, geriatric oral surgery requires a holistic, patient-centered, multidisciplinary approach focused not only on surgical success but also on preservation of function, independence, comfort, and quality of life.

References

- United Nations. World Population Ageing Report. United Nations; 2020.
- Ettinger RL. Oral health and the aging population. *J Am Dent Assoc.* 2007;138:5S-6S.
- Papas A, Niessen LC, Chauncey HH. *Geriatric Dentistry.* Mosby; 1991.
- Maher RL, Hanlon J, Hajjar ER. Clinical consequences of polypharmacy in elderly. *Expert Opin Drug Saf.* 2014;13:57-65.
- Fried LP, Tangen CM, Walston J, Newman AB, Hirsch C, Gottdiener J, et al. Frailty in older adults. *J Gerontol A Biol Sci Med Sci.* 2001;56:M146-M156.
- Petersen PE, Yamamoto T. Improving oral health of older people. *Community Dent Oral Epidemiol.* 2005;33:81-92.
- Müller F, Schimmel M. Revised success criteria for implant prostheses in older adults. *Int J Prosthodont.* 2016;29:449-454.
- Holm-Pedersen P, Løe H. *Geriatric Dentistry.* Wiley Blackwell; 2015.
- Marchini L, Ettinger R. The complexity of oral health care in older adults. *Dent Clin North Am.* 2014;58:757-772.
- Razak PA, Richard KMJ, Thankachan RP, Hafiz KAA, Kumar KN, Sameer KM. Geriatric oral health. *J Int Oral Health.* 2014;6:110-116.
- Lakatta EG. Cardiovascular aging research. *Circulation.* 2003;107:346-354.
- Aronow WS. Management of cardiovascular disease in elderly patients. *J Gerontol A Biol Sci Med Sci.* 2002;57:M397-M404.
- Janssens JP, Pache JC, Nicod LP. Physiological changes in respiratory system with aging. *Eur Respir J.* 1999;13:197-205.
- Hazzard WR. *Principles of Geriatric Medicine and Gerontology.* McGraw Hill; 2003.
- Lindeman RD. Renal physiology and aging. *J Am Geriatr Soc.* 1990;38:278-285.
- Schmucker DL. Liver function and phase I drug metabolism in aging. *Drugs Aging.* 2001;18:837-851.
- Pawelec G. Immunosenescence and aging. *Exp Gerontol.* 2014;54:1-5.
- Seeman E. Pathogenesis of bone fragility in women and men. *Lancet.* 2002;359:1841-1850.

- Makary MA, Segev DL, Pronovost PJ, Syin D, Bandeen-Roche K, Patel P, et al. Frailty as predictor of surgical outcomes. *J Am Coll Surg*. 2010;210:901-908.
- Reuben DB, Rubenstein LV, Hirsch SH, Hays RD. Value of functional status as predictor in elderly. *Am J Med*. 1992;93:663-669.
- Hajjar ER, Cafiero AC, Hanlon JT. Polypharmacy in elderly patients. *Am J Geriatr Pharmacother*. 2007;5:345-351.
- Steinman MA, Hanlon JT. Managing medications in clinically complex elders. *JAMA*. 2010;304:1592-1601.
- Inouye SK. Delirium in older persons. *N Engl J Med*. 2006;354:1157-1165.
- Morley JE. Undernutrition in older adults. *Fam Pract*. 2012;29:i89-i93.
- Clegg A, Young J, Iliffe S, Rikkert MO, Rockwood K. Frailty in elderly people. *Lancet*. 2013;381:752-762.
- Gurwitz JH. Polypharmacy and prescribing quality in older people. *J Am Geriatr Soc*. 2004;52:1515-1516.
- Turnheim K. Drug therapy in the elderly. *Exp Gerontol*. 2004;39:1731-1738.
- Wahl MJ. Dental surgery in anticoagulated patients. *Arch Intern Med*. 1998;158:1610-1616.
- Nematullah A, Alabousi A, Blanas N, Douketis JD, Sutherland SE. Dental surgery for patients on anticoagulants. *J Can Dent Assoc*. 2009;75:41-47.
- Brennan MT, Wynn RL, Miller CS. Aspirin and bleeding in oral surgery. *Oral Surg Oral Med Oral Pathol Oral Radiol Endod*. 2007;104:316-323.
- Ruggiero SL, Dodson TB, Fantasia J, Goodday R, Aghaloo T, Mehrotra B, et al. Medication-related osteonecrosis of the jaw update. *J Oral Maxillofac Surg*. 2014;72:1938-1956.
- Marx RE. Pamidronate and zoledronate induced avascular necrosis. *J Oral Maxillofac Surg*. 2003;61:1115-1117.
- American Geriatrics Society. Pharmacological management of persistent pain in older persons. *J Am Geriatr Soc*. 2009;57:1331-1346.
- Mangoni AA, Jackson SHD. Age-related changes in pharmacokinetics and pharmacodynamics. *Br J Clin Pharmacol*. 2004;57:6-14.
- Turnheim K. When drug therapy gets old. *Exp Gerontol*. 2003;38:843-853.

- McCaul LK. Oral surgery in elderly patients. *Dent Update*. 2012;39:98-104.
- Krimmel M, Reinert S. Mandibular fractures in elderly patients. *J Oral Maxillofac Surg*. 2000;58:1115-1119.
- Sacco R, Sacco M, Carpenedo M, Moia M. Oral surgery and anticoagulant therapy. *Thromb Haemost*. 2007;97:549-553.
- Carter G, Goss A. Tranexamic acid mouthwash versus autologous fibrin glue. *Int J Oral Maxillofac Surg*. 2003;32:504-507.
- Fragiskos FD. *Oral Surgery*. Springer; 2007.
- Moy PK, Medina D, Shetty V, Aghaloo TL. Dental implant failure rates and associated risk factors. *Int J Oral Maxillofac Implants*. 2005;20:569-577.
- Srinivasan M, Meyer S, Mombelli A, Müller F. Dental implants in elderly patients. *Clin Oral Implants Res*. 2017;28:920-930.
- Bornstein MM, Cionca N, Mombelli A. Systemic conditions and implant therapy. *Int J Oral Maxillofac Implants*. 2009;24:12-27.
- Holahan CM, Koka S, Kennel KA, Weaver AL, Assad DA, Regennitter FJ. Implant survival in osteoporotic patients. *Int J Oral Maxillofac Implants*. 2008;23:687-693.
- Fortin T, Bosson JL, Isidori M, Blanchet E. Effect of flapless surgery on implant rehabilitation. *Int J Oral Maxillofac Implants*. 2006;21:298-304.
- Müller F, Schimmel M. Implant prosthodontics in elderly patients. *Gerodontology*. 2010;27:213-218.
- Awad MA, Lund JP, Dufresne E, Feine JS. Oral health-related quality of life and implant overdentures. *J Dent Res*. 2003;82:39-43.
- Ruggiero SL, Dodson TB, Assael LA, Landesberg R, Marx RE, Mehrotra B. Osteonecrosis of the jaw associated with bisphosphonates. *J Oral Maxillofac Surg*. 2009;67:2-12.
- Otto S, Marx RE, Tröltzsch M, Ristow O, Ziebart T, Al-Nawas B, et al. Bisphosphonate-related osteonecrosis. *Oral Maxillofac Surg*. 2015;19:177-195.
- Khan AA, Morrison A, Hanley DA, Felsenberg D, McCauley LK, O’Ryan F, et al. International consensus on osteonecrosis of the jaw. *J Bone Miner Res*. 2015;30:3-23.

- Nicolatou-Galitis O, Schiodt M, Mendes RA, Ripamonti C, Hope S, Drudge-Coates L, et al. Medication-related osteonecrosis in cancer patients. *Support Care Cancer*. 2019;27:3835-3847.
- Saad F, Brown JE, Van Poznak C, Ibrahim T, Stemmer SM, Stopeck AT, et al. Incidence and risk factors for osteonecrosis. *Ann Oncol*. 2012;23:1341-1347.
- Yarom N, Shapiro CL, Peterson DE, Van Poznak CH, Bohlke K, Ruggiero SL, et al. Prevention and management of osteonecrosis. *J Clin Oncol*. 2019;37:2270-2290.
- Otto S, Pautke C, Opelz C, Westphal I, Drosse I, Schwager J, et al. Osteonecrosis prevention in elderly patients. *J Craniomaxillofac Surg*. 2011;39:142-147.
- Vescovi P, Merigo E, Meleti M, Manfredi M, Guidotti R, Nammour S. Laser therapy and platelet concentrates in MRONJ. *Photomed Laser Surg*. 2012;30:179-184.
- Warnakulasuriya S. Global epidemiology of oral cancer. *Oral Oncol*. 2009;45:309-316.
- Petersen PE. Oral cancer prevention and control. *Oral Oncol*. 2009;45:454-460.
- Neville BW, Day TA. Oral cancer and precancerous lesions. *CA Cancer J Clin*. 2002;52:195-215.
- Seoane J, Varela-Centelles PI, Diz-Dios P, De la Cruz J, Ramirez JR, Cameselle-Teijeiro J. Delayed diagnosis of oral cancer. *Oral Oncol*. 2004;40:388-394.
- Silverman S Jr. Demographics and occurrence of oral cancer. *Oral Surg Oral Med Oral Pathol Oral Radiol Endod*. 2001;91:517-526.
- Pignon JP, Bourhis J, Domenge C, Designé L. Chemotherapy added to locoregional treatment for head and neck cancer. *Lancet*. 2000;355:949-955.
- Extermann M. Interaction between comorbidity and cancer. *Cancer Control*. 2007;14:13-22.
- Gerbino G, Roccia F, De Giovanni PP, Berrone S. Maxillofacial trauma in elderly patients. *J Oral Maxillofac Surg*. 1999;57:777-782.
- Sterling DA, O'Connor JA, Bonadies J. Geriatric falls. *Ann Emerg Med*. 2001;38:430-435.
- Toivari M, Helenius M, Suominen AL, Lindqvist C, Thorén H. Facial fractures in elderly patients. *Injury*. 2010;41:1308-1311.
- Bruce RA, Ellis E III. Management of fractures in edentulous mandibles. *J Oral Maxillofac Surg*. 1993;51:494-500.

- Ellis E III. Treatment methods for fractures of the mandibular angle. *Int J Oral Maxillofac Surg.* 1999;28:243-252.
- Lennox P, Cobb T, Knowles C. Geriatric trauma and rehabilitation. *Clin Geriatr Med.* 2006;22:161-177.
- Chrcanovic BR. Fixation techniques in mandibular fractures. *Oral Maxillofac Surg.* 2013;17:95-104.
- Dodds C. Physiology of aging and anesthesia. *Int Anesthesiol Clin.* 2001;39:1-20.
- Crome P, Lally F, Cherubini A, Oristrell J, Beswick AD, Clarfield AM, et al. Exclusion of older people from clinical trials. *Drugs Aging.* 2011;28:667-677.
- Malamed SF. *Handbook of Local Anesthesia.* 7th ed. Elsevier; 2020.
- Haas DA. An update on local anesthetics in dentistry. *J Can Dent Assoc.* 2002;68:546-551.
- Dundee JW, Halliday NJ, Harper KW, Brogden RN. Midazolam: a review of pharmacological properties. *Drugs.* 1984;28:519-543.
- Marcantonio ER. Postoperative delirium. *N Engl J Med.* 2017;377:1456-1466.
- Pompei P, Foreman M, Rudberg MA, Inouye SK, Braund V, Cassel CK. Delirium in hospitalized older persons. *Arch Intern Med.* 1994;154:334-340.
- American Geriatrics Society Panel on Persistent Pain in Older Persons. Clinical practice guidelines. *J Am Geriatr Soc.* 2002;50:S205-S224.
- Sullivan DH. Nutrition and aging. *Am J Clin Nutr.* 1995;61:262S-265S.
- Weinberg AD, Minaker KL. Dehydration in elderly patients. *JAMA.* 1995;274:1552-1556.
- Hupp JR, Ellis E III, Tucker MR. *Contemporary Oral and Maxillofacial Surgery.* 7th ed. Elsevier; 2019.
- Ship JA, Pillemer SR, Baum BJ. Xerostomia and oral health in elderly. *J Am Geriatr Soc.* 2002;50:535-543.
- Beauchamp TL, Childress JF. *Principles of Biomedical Ethics.* Oxford University Press; 2013.
- Fried TR, Bradley EH, Towle VR, Allore H. Understanding treatment preferences of older patients. *N Engl J Med.* 2002;346:1061-1066.
- Elwyn G, Frosch D, Thomson R, Joseph-Williams N, Lloyd A, Kinnersley P, et al. Shared decision making. *J Gen Intern Med.* 2012;27:1361-1367.

- Locker D. Measuring oral health-related quality of life. *Community Dent Health*. 1988;5:3-18.
- Saunders C. The management of terminal malignant disease. Edward Arnold; 1978.
- United Nations. World Population Prospects. United Nations; 2022.
- Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry. *J Dent Res*. 2020;99:769-774.
- Partridge JSL, Harari D, Martin FC, Dhesi JK. Frailty assessment in surgical patients. *Age Ageing*. 2012;41:142-147.
- Miron RJ, Choukroun J. Platelet Rich Fibrin in Regenerative Dentistry. Wiley Blackwell; 2017.
- Ghai S. Teledentistry during COVID-19 pandemic. *Oral Dis*. 2020;27:239-241.
- Ettinger RL. Meeting oral health needs to promote well-being in older adults. *J Am Dent Assoc*. 2018;149:1-3.

CHAPTER 2

TRAUMATIC DENTAL INJURIES IN THE PRIMARY DENTITION

Sıla Beren ADIGÜZEL ERDOĞAN¹

¹ Uzm. Dt. ORCID ID: 0009-0001-9030-5179

1. Introduction

Traumatic dental injuries (TDIs) are common oral health problems during childhood and may affect the teeth, periodontal tissues, and surrounding supporting structures. In the primary dentition, these injuries are particularly important because they frequently occur during the early years of life, a period characterized by rapid physical development and increasing motor activity (Petti, Glendor, & Andersson, 2018). Falls and collisions are among the most common causes of traumatic injuries in young children, and the maxillary primary incisors are particularly susceptible because of their anterior position in the dental arch. Although injuries to primary teeth are often regarded as temporary problems because these teeth will eventually exfoliate, their clinical consequences may extend beyond the primary dentition. Pain, functional impairment, aesthetic concerns, pulpal and periodontal complications, and potential disturbances in the development of the permanent successor make appropriate diagnosis, management, and follow-up essential (Fitzgibbon, Carli, Piana, Montevecchi, & Bagattoni, 2023).

A distinctive feature of traumatic dental injuries in the primary dentition is the close anatomical relationship between the roots of primary teeth and the developing permanent tooth germs. Consequently, trauma to a primary tooth may affect not only the injured tooth itself but also the development of its permanent successor. The type and severity of developmental disturbances are influenced by several factors, including the child's age at the time of injury, the type and severity of trauma, and the developmental stage of the permanent tooth germ (Caeiro-Villasenin et al., 2022). Reported sequelae include enamel discoloration and hypoplasia, crown or root dilaceration, disturbances in root development, odontoma-like malformations, and alterations in the eruption pathway. Luxation injuries, particularly intrusion and avulsion, have traditionally been associated with a greater risk of developmental disturbances because of their potential to transmit traumatic forces directly to the developing permanent tooth germ. Therefore, the possible effects on the permanent successor should always be considered during the assessment and long-term follow-up of traumatic injuries to primary teeth (Folmer, Lauridsen, Henriksen, & Hermann, 2025; Petti et al., 2018).

The management of traumatic dental injuries in the primary dentition requires a different approach from that used for permanent teeth. Treatment decisions should consider not only the type and severity of the injury but also the child's age, maturity, ability to cooperate, stage of root development and physiological resorption, expected time of exfoliation, and the potential effects of treatment on the developing permanent successor (Day et al., 2020). In young

children, the first dental visit following trauma may be associated with considerable fear and anxiety, which can make clinical and radiographic examination as well as treatment challenging (Day et al., 2020). Therefore, management should aim to relieve pain, promote healing, maintain function whenever possible, and minimize both psychological distress and the risk of further injury to the permanent tooth germ. In many situations, particularly when there is no risk of aspiration or ingestion and no significant interference with occlusion, observation and careful follow-up may be preferable to immediate invasive treatment. Accordingly, an individualized and child-centered approach, combined with appropriate parental guidance and long-term monitoring, is fundamental to the successful management of traumatic injuries in the primary dentition (Petti et al., 2018).

Given the potential short- and long-term consequences of traumatic dental injuries in young children, accurate diagnosis, appropriate management, and systematic follow-up are essential for achieving favorable outcomes. A comprehensive understanding of injury patterns and healing responses is also important for recognizing complications at an early stage and protecting the developing permanent dentition. This chapter provides an overview of traumatic dental injuries in the primary dentition, with particular emphasis on their epidemiology and etiology, classification, clinical and radiographic assessment, management according to injury type, follow-up protocols, potential complications, and developmental consequences for permanent successors.

2. Epidemiology and Etiology

Traumatic dental injuries are highly prevalent during early childhood and constitute an important component of pediatric oral health care. Epidemiological studies have reported considerable variation in the prevalence of traumatic injuries in the primary dentition, partly because of differences in study populations, age ranges, diagnostic criteria, and trauma classification systems. A global meta-analysis estimated the prevalence of traumatic dental injuries in the primary dentition to be 22.7%. Similarly, a subsequent systematic review and meta-analysis including 22,839 children aged 0–6 years reported an overall prevalence of 24.2%. These findings indicate that approximately one in four children may experience a traumatic injury involving the primary dentition. Nevertheless, prevalence estimates should be interpreted cautiously because substantial heterogeneity exists among epidemiological studies and the certainty of the available evidence remains limited (Patnana et al., 2021; Petti et al., 2018).

Traumatic dental injuries in the primary dentition occur most frequently during the first years of life, particularly when children begin to walk, run, and explore their environment independently. The increased mobility combined with immature motor coordination and limited ability to recognize potential hazards makes young children particularly susceptible to falls and collisions (Patnana et al., 2021). The anterior region of the maxilla is the most commonly affected area, with the maxillary primary central incisors accounting for the majority of injured teeth (Agouropoulos et al., 2021; Gümüş, Öztürk, & Kürem, 2021). Their prominent position in the dental arch and greater exposure to direct impact contribute to this susceptibility. Although some epidemiological studies have reported a higher frequency of traumatic dental injuries among boys, sex-related differences in the primary dentition are not consistent across studies (Patnana et al., 2021). This may reflect the relatively similar patterns of physical activity and environmental exposure among boys and girls during early childhood (Mordini, Lee, Lazaro, Biagi, & Giannetti, 2021).

Falls are the most common cause of traumatic dental injuries in the primary dentition, particularly during the early years of childhood. Other reported causes include collisions, play-related accidents, sports activities, traffic accidents, and, less frequently, violence. The etiology may vary according to the child's age, developmental stage, environment, and level of physical activity. Therefore, identifying the mechanism of injury remains an important component of trauma assessment and may also provide relevant information regarding the severity and pattern of the injury (Burns & Malcolm, 2023).

3. Classification of Traumatic Dental Injuries

Traumatic dental injuries comprise a broad spectrum of conditions involving the tooth, periodontal tissues, supporting bone, and surrounding soft tissues. Accurate classification of the injury is essential for establishing the diagnosis, selecting an appropriate treatment approach, and planning follow-up. In the primary dentition, traumatic dental injuries can generally be classified according to the tissues involved into injuries to the dental hard tissues and pulp, injuries to the periodontal tissues, injuries to the supporting bone, and injuries to the gingiva or oral mucosa (Feliciano & Caldas Jr, 2006).

Injuries to the dental hard tissues and pulp include enamel fractures, enamel–dentin fractures, complicated crown fractures involving the pulp, crown–root fractures, and root fractures. Periodontal tissue injuries include concussion, subluxation, extrusive luxation, lateral luxation, intrusive luxation, and avulsion (Lam, 2016). Supporting tissue injuries mainly include fractures of the alveolar process, while associated soft-tissue injuries may present as abrasions,

contusions, or lacerations of the gingiva and oral mucosa. More than one type of injury may occur simultaneously; therefore, both the injured tooth and the surrounding tissues should be systematically evaluated.

4. Clinical and Radiographic Examination

A systematic assessment is essential for the accurate diagnosis and appropriate management of traumatic dental injuries in the primary dentition. A detailed history should include the time, location, and mechanism of the injury, as well as any previous dental trauma and relevant medical history. Information regarding loss of consciousness, vomiting, headache, amnesia, or other neurological symptoms should also be obtained, as these findings may indicate an associated head injury requiring medical evaluation. The circumstances surrounding the injury should be carefully documented, particularly when the reported history is inconsistent with the clinical findings or when non-accidental injury is suspected. In addition, the child's general condition, pain, behavior, and ability to cooperate should be assessed before proceeding with a detailed dental examination (Lam, 2016).

5. Management of Traumatic Dental Injuries in Primary Teeth

The management of traumatic dental injuries in the primary dentition should aim to relieve pain, promote healing, preserve the primary tooth when appropriate, and minimize the risk of damage to the developing permanent successor. Treatment decisions depend on the type and severity of the injury, the child's age and ability to cooperate, the degree of tooth displacement and mobility, occlusal interference, stage of root development or physiological resorption, and the presence of associated soft-tissue or alveolar injuries. Whenever possible, a conservative approach is preferred, particularly in young children, provided that the injured tooth does not pose a risk of aspiration or ingestion and does not interfere with occlusion. Parents or caregivers should be informed about the expected course of healing, possible complications, home-care measures, and the importance of attending scheduled follow-up visits (Nashkova & Dimova, 2022).

5.1. Crown Fractures

Crown fractures in primary teeth may involve enamel alone, enamel and dentin, or enamel and dentin with pulp exposure. Enamel fractures generally require no active treatment other than smoothing sharp or irregular edges when necessary. In enamel–dentin fractures without pulp exposure, exposed dentin should be covered with a suitable restorative material, such as glass ionomer cement or composite resin, to protect the underlying pulp and restore the tooth when indicated. If a tooth fragment is missing, the surrounding soft tissues should be carefully

examined, particularly when lacerations are present, because fragments may occasionally become embedded in the lips, cheeks, or tongue (Aartman, van Everdingen, Hoogstraten, & Schuurs, 1996).

Complicated crown fractures involve enamel and dentin with exposure of the pulp. Whenever feasible, preservation of pulp vitality should be the primary objective. Partial pulpotomy is generally recommended, while cervical pulpotomy may be considered when the pulp exposure is extensive. The choice of treatment should also take into account the child's age, cooperation, stage of root development, restorability of the tooth, and expected time to physiological exfoliation. Following treatment, clinical follow-up is important to identify signs of pulpal necrosis or infection, such as persistent symptoms, swelling, sinus tract formation, increased mobility, or persistent dark-gray discoloration associated with other signs of infection (Andreasen, Andreasen, Skeie, Hjørting-Hansen, & Schwartz, 2002).

5.2. Crown–Root Fractures and Root Fractures

Crown–root fractures involve enamel, dentin, and cementum and may occur with or without pulp exposure. Clinically, the fractured coronal fragment may remain attached to the tooth but exhibit varying degrees of mobility, often causing pain during biting or chewing. Management depends on the extent of the fracture, pulp involvement, restorability of the tooth, and the child's ability to cooperate. When the tooth is restorable, removal of the loose fragment followed by appropriate restorative or pulp treatment may be considered (Spinas et al., 2022). However, extraction may be necessary when the fracture extends deeply below the gingival margin, the tooth cannot be predictably restored, or the remaining fragments present a risk of aspiration or ingestion. Care should be taken during extraction to minimize potential damage to the developing permanent successor.

Root fractures involve the dentin, cementum, and pulp and may occur in the apical, middle, or cervical third of the root. Clinical findings vary according to the fracture location and may include mobility or displacement of the coronal fragment, gingival bleeding, and discomfort during function. When the coronal fragment is not displaced, observation without active intervention is generally recommended. In cases of displacement, treatment depends on the degree of mobility, occlusal interference, and the risk of aspiration or ingestion. Spontaneous repositioning may be allowed in selected cases, whereas extraction of the coronal fragment may be indicated when it is excessively mobile or interferes with occlusion. The apical fragment should generally be left in place to undergo physiological resorption rather than being surgically removed. Regular clinical follow-up is essential to monitor healing and identify complications

such as pulp necrosis, infection, or pathological root resorption (Kevci, Gerds, Lauridsen, & Andersson, 2023).

5.3. Periodontal Tissue Injuries (Luxation Injuries)

5.3.1 Concussion and Subluxation

Concussion and subluxation are traumatic injuries affecting the periodontal supporting tissues without displacement of the tooth. Concussion is characterized by tenderness to percussion without increased mobility or bleeding from the gingival sulcus. In contrast, subluxation involves increased tooth mobility without displacement and may be accompanied by bleeding from the gingival sulcus. Radiographic findings are generally unremarkable in both injuries, although baseline radiographs may be obtained when clinically indicated. Neither concussion nor subluxation usually requires active treatment, and observation is the preferred approach. Parents should be advised to maintain good oral hygiene and minimize additional trauma to the affected area during healing. Clinical follow-up is recommended to monitor pulpal and periodontal healing and to identify potential complications, including pulp necrosis, infection, or persistent discoloration. According to the International Association of Dental Traumatology guidelines, clinical follow-up is recommended after one week for concussion and after one week and six to eight weeks for subluxation (Kevci et al., 2023).

5.3.2 Extrusive Luxation

Extrusive luxation is characterized by partial displacement of the tooth out of its alveolar socket along its longitudinal axis, resulting in an elongated clinical appearance and increased mobility. Bleeding from the gingival sulcus and discomfort during occlusion may also be observed. Radiographic examination may reveal widening of the periodontal ligament space, particularly in the apical region. Treatment decisions depend on the degree of extrusion, tooth mobility, occlusal interference, root development, and the child's ability to cooperate. In cases of minor extrusion without significant occlusal interference, spontaneous repositioning may be allowed under careful observation. However, extraction is generally recommended when the tooth is excessively mobile or severely extruded, particularly when the risk of aspiration or ingestion is present. During extraction, care should be taken to avoid damage to the developing permanent tooth germ. Regular follow-up is essential to evaluate periodontal healing and identify complications such as pulp necrosis, infection, and pathological root resorption. According to the International Association of Dental Traumatology guidelines, clinical follow-up is recommended after one week, six to eight weeks, and one year (Lauridsen, Blanche, Yousaf, & Andreasen, 2017).

5.3.3 Lateral Luxation

Lateral luxation is characterized by displacement of the tooth in a direction other than its longitudinal axis, often accompanied by compression or fracture of the alveolar socket wall. Clinically, the affected tooth may appear displaced in a labial or palatal direction and is frequently immobile because the root apex becomes locked within the alveolar bone. Bleeding from the gingival sulcus and occlusal interference may also be observed (Day et al., 2020). Radiographic examination may reveal widening of the periodontal ligament space, depending on the direction of displacement. Management is primarily determined by the severity of displacement and the presence of occlusal interference. In cases of minimal displacement without occlusal interference, spontaneous repositioning may be allowed, and the tooth should be monitored for improvement in its position over the following months. For severely displaced teeth, particularly when the tooth interferes with occlusion, gentle repositioning by an experienced clinician or extraction may be considered. Repositioning may require a flexible splint if the tooth remains unstable. Clinical follow-up is recommended after one week, six to eight weeks, six months, and one year to evaluate periodontal healing and identify complications such as pulp necrosis, infection, or pathological root resorption (Lauridsen et al., 2017).

5.3.4. Intrusive Luxation

Intrusive luxation is a severe traumatic injury characterized by the axial displacement of a tooth into the alveolar bone, resulting in partial or complete disappearance of the clinical crown. The injury is frequently accompanied by compression or fracture of the alveolar socket and damage to the periodontal ligament and neurovascular structures. Clinically, the affected tooth appears shortened or may be completely embedded within the alveolar socket. Radiographic examination is important for assessing the position of the intruded tooth, the direction of root displacement, and its relationship with the developing permanent successor (Lauridsen et al., 2017). Due to the close anatomical proximity between primary tooth roots and permanent tooth germs, intrusive injuries are associated with an increased risk of developmental disturbances in the permanent dentition.

According to the International Association of Dental Traumatology guidelines, spontaneous re-eruption is recommended for intruded primary teeth regardless of the direction of displacement. Most intruded primary teeth are expected to re-erupt spontaneously within six months, although re-eruption may occasionally take up to one year. Immediate surgical repositioning or extraction solely on the basis of the direction of root displacement is no longer recommended.

Nevertheless, extraction may become necessary if complications such as infection, progressive pathological root resorption, or other unfavorable clinical findings develop (Gurunathan, Murugan, & Somasundaram, 2016). Regular clinical and radiographic follow-up is essential to assess re-eruption, periodontal healing, and potential complications. Clinical follow-up is recommended after one week, six to eight weeks, six months, and one year, with additional monitoring when indicated. Parents should be informed about the possibility of developmental disturbances affecting the permanent successor and the importance of long-term observation.

5.3.4 Avulsion

Avulsion is defined as the complete displacement of a tooth from its alveolar socket following traumatic injury, resulting in disruption of the periodontal ligament and neurovascular structures. Clinically, the affected tooth is absent from the dental arch, and bleeding from the empty socket may be observed. A careful clinical examination and detailed trauma history are essential to distinguish avulsion from complete intrusion or other causes of a missing tooth. If the avulsed tooth cannot be located, the possibility of aspiration, ingestion, or displacement into the surrounding soft tissues should be considered, and appropriate investigations should be performed when indicated (Christophersen, Freund, & Harild, 2005).

Unlike permanent teeth, avulsed primary teeth should never be replanted because of the potential risk of damaging the developing permanent tooth germ, the possibility of treatment-related complications, and the limited feasibility of replantation in young children (Lenzi, Alexandria, Ferreira, & Maia, 2015). Management generally involves examination of the socket and surrounding tissues, control of bleeding, pain management, and appropriate parental guidance. Caregivers should be advised to maintain good oral hygiene, provide a soft diet when necessary, and monitor the injured area for signs of infection or abnormal healing. According to the International Association of Dental Traumatology guidelines, clinical follow-up is recommended after six to eight weeks, with additional monitoring of the developing permanent successor when indicated. Parents should be informed about possible developmental disturbances, including enamel defects, crown or root malformations, and eruption abnormalities, which may become apparent only after the permanent tooth erupts (Lenzi et al., 2015).

6. Follow-up and Prognosis

Follow-up is an essential component of the management of traumatic dental injuries in the primary dentition, as complications may develop weeks, months, or even years after the initial injury. The frequency and duration of follow-up should be determined according to the type

and severity of the injury, the treatment performed, and the presence of clinical or radiographic abnormalities. Clinical evaluation should focus on pain, swelling, tooth discoloration, abnormal mobility, sinus tract formation, and signs of infection or pathological root resorption. Although discoloration may occur following trauma, it does not necessarily indicate pulp necrosis in the absence of other clinical or radiographic signs of infection. Radiographic examinations should be performed when clinically indicated rather than routinely at every follow-up visit (Lauridsen et al., 2017; Lenzi et al., 2015).

The prognosis of traumatized primary teeth depends on several factors, including the type and severity of injury, the stage of root development or physiological resorption, and the condition of the surrounding periodontal tissues. While many injuries heal without significant complications, severe luxation injuries may result in pulpal or periodontal complications and developmental disturbances in the permanent successors. Therefore, long-term monitoring of the developing permanent dentition is particularly important following severe traumatic injuries (Lauridsen et al., 2017). Parents should be informed about potential complications and encouraged to seek dental care if unfavorable signs develop. Appropriate follow-up and early identification of complications are essential for maintaining oral health and minimizing the long-term consequences of traumatic dental injuries.

7. Conclusion

Traumatic dental injuries in the primary dentition represent an important clinical concern due to their potential effects on both primary teeth and developing permanent successors. Accurate diagnosis, appropriate injury-specific management, and regular follow-up are essential for achieving favorable outcomes. A conservative and child-centered approach should be prioritized whenever clinically appropriate, with particular attention to minimizing discomfort, preventing complications, and protecting the developing permanent dentition. Furthermore, parental education and awareness of potential long-term consequences play a crucial role in successful management. Adherence to evidence-based guidelines and individualized treatment planning can contribute to improved clinical outcomes and reduce the risk of adverse consequences following traumatic dental injuries in young children.

REFERENCES

- Aartman, I. H., van Everdingen, T., Hoogstraten, J., & Schuurs, A. H. (1996). Appraisal of behavioral measurement techniques for assessing dental anxiety and fear in children: A review. *Journal of Psychopathology and Behavioral Assessment*, 18, 153-171.
- Agouropoulos, A., Pavlou, N., Kotsanti, M., Gourtsogianni, S., Tzanetakis, G., & Gizani, S. (2021). A 5-year data report of traumatic dental injuries in children and adolescents from a major dental trauma center in Greece. *Dental Traumatology*, 37(4), 631-638.
- Andreasen, J., Andreasen, F., Skeie, A., Hjørting-Hansen, E., & Schwartz, O. (2002). Effect of treatment delay upon pulp and periodontal healing of traumatic dental injuries—a review article. *Dental Traumatology*, 18(3), 116-128.
- Burns, B., & Malcolm, L. (2023). A review of the IADT 2020 guidelines. *Primary Dental Journal*, 12(4), 22-27.
- Caeiro-Villasenín, L., Serna-Munoz, C., Perez-Silva, A., Vicente-Hernandez, A., Poza-Pascual, A., & Ortiz-Ruiz, A. J. (2022). Developmental dental defects in permanent teeth resulting from trauma in primary dentition: a systematic review. *International Journal of Environmental Research and Public Health*, 19(2), 754.
- Christophersen, P., Freund, M., & Harild, L. (2005). Avulsion of primary teeth and sequelae on the permanent successors. *Dental Traumatology*, 21(6), 320-323.
- Day, P. F., Flores, M. T., O'Connell, A. C., Abbott, P. V., Tsilingaridis, G., Fouad, A. F., . . . Hicks, L. (2020). International Association of Dental Traumatology guidelines for the management of traumatic dental injuries: 3. Injuries in the primary dentition. *Dental Traumatology*, 36(4), 343-359.
- Feliciano, K. M. P. d. C., & Caldas Jr, A. d. F. (2006). A systematic review of the diagnostic classifications of traumatic dental injuries. *Dental Traumatology*, 22(2), 71-76.
- Fitzgibbon, R., Carli, E., Piana, G., Montevecchi, M., & Bagattoni, S. (2023). Dental trauma epidemiology in primary dentition: A cross-sectional retrospective study. *Applied Sciences*, 13(3), 1878.
- Folmer, A. M., Lauridsen, E., Henriksen, J. S., & Hermann, N. V. (2025). Sequelae in Permanent Dentition After Traumatic Dental Injury in the Primary Dentition—A Retrospective Cohort Study. *International Journal of Paediatric Dentistry*, 35(5), 878-887.
- Gurunathan, D., Murugan, M., & Somasundaram, S. (2016). Management and sequelae of intruded anterior primary teeth: a systematic review. *International journal of clinical pediatric dentistry*, 9(3), 240.
- Gümüş, H., Öztürk, G., & Kürem, B. (2021). Profiles of traumatic dental injuries among children aged 0–15 years in Cappadocia, Turkey: A retrospective cohort study. *Dental Traumatology*, 37(3), 419-429.
- Kevci, M., Gerds, T. A., Lauridsen, E., & Andersson, L. (2023). The risk of healing complications in primary teeth with root fractures: A retrospective cohort study. *Dental Traumatology*, 39(5), 455-461.
- Lam, R. (2016). Epidemiology and outcomes of traumatic dental injuries: a review of the literature. *Australian dental journal*, 61, 4-20.
- Lauridsen, E., Blanche, P., Yousaf, N., & Andreasen, J. O. (2017). The risk of healing complications in primary teeth with extrusive or lateral luxation—a retrospective cohort study. *Dental Traumatology*, 33(4), 307-316.

- Lenzi, M. M., Alexandria, A. K., Ferreira, D. M. T., & Maia, L. C. (2015). Does trauma in the primary dentition cause sequelae in permanent successors? A systematic review. *Dental Traumatology*, 31(2), 79-88.
- Mordini, L., Lee, P., Lazaro, R., Biagi, R., & Giannetti, L. (2021). Sport and dental traumatology: Surgical solutions and prevention. *Dentistry journal*, 9(3), 33.
- Nashkova, S., & Dimova, C. (2022). Traumatic dental injuries: etiology, prevalence and possible outcomes. *MEDIS–International Journal of Medical Sciences and Research*, 1(4), 27-29.
- Patnana, A. K., Chugh, A., Chugh, V. K., Kumar, P., Vanga, N. R. V., & Singh, S. (2021). The prevalence of traumatic dental injuries in primary teeth: a systematic review and meta-analysis. *Dental Traumatology*, 37(3), 383-399.
- Petti, S., Glendor, U., & Andersson, L. (2018). World traumatic dental injury prevalence and incidence, a meta-analysis—One billion living people have had traumatic dental injuries. *Dental Traumatology*, 34(2), 71-86.
- Spinas, E., Di Giorgio, G., Murgia, M. S., Garau, V., Pinna, M., & Zerman, N. (2022). Root fractures in the primary teeth and their management: a scoping review. *Dentistry journal*, 10(5), 74.

CHAPTER 3

MACHINE LEARNING AND PREDICTIVE ANALYTICS IN IMPLANT DENTISTRY

Özge ÖZDAL ZİNCİR¹

¹ Assoc. Prof. Dr. Istanbul University- Cerrahpasa Faculty of Dentistry, Department of Oral and Maxillofacial Surgery ORCID: 0009-0000-9423-5764

Introduction

Machine learning and predictive analytics are increasingly transforming modern healthcare by enabling data-driven clinical decision-making, individualized risk assessment, and outcome prediction. In implant dentistry, these technologies have attracted substantial attention because implant success depends on complex interactions among biological, surgical, prosthetic, biomechanical, and behavioral variables that are often difficult to evaluate simultaneously using conventional clinical methods [1].

Dental implant therapy has become one of the most predictable and successful treatment modalities for rehabilitation of partially and completely edentulous patients. Advances in implant surface technologies, digital workflows, regenerative procedures, biomaterials, and guided surgery have significantly improved long-term clinical outcomes during recent decades [2]. Nevertheless, implant failures, peri-implantitis, prosthetic complications, and marginal bone loss continue to occur despite modern treatment protocols.

Traditional prognostic assessment in implant dentistry generally relies on clinician experience, radiographic interpretation, medical history evaluation, and population-based statistical evidence [3]. Although these methods remain clinically valuable, they may not fully capture the complex nonlinear relationships that exist among multiple patient-specific risk factors.

Machine learning provides computational methods capable of learning patterns from clinical data and generating predictive models that improve through iterative training processes [4]. These algorithms may analyze large multidimensional datasets and identify subtle relationships that may not be readily detectable through traditional statistical analyses.

Predictive analytics refers to the application of statistical, computational, and machine learning methods to estimate future outcomes based on historical and real-time information [5]. In implant dentistry, predictive systems may potentially estimate implant survival probability, identify patients at increased risk for peri-implantitis, forecast prosthetic complications, and support individualized treatment planning.

The increasing integration of electronic health records, cone-beam computed tomography, intraoral scanners, digital implant planning systems, and large clinical databases has created favorable conditions for development of machine learning applications in implant dentistry [6].

Artificial intelligence is frequently used as a broad umbrella term describing computational systems capable of performing tasks requiring human-like intelligence. Machine learning represents one of the major subsets of artificial intelligence and specifically focuses on data-driven learning algorithms [7]. Deep learning, another important subfield, utilizes multilayer neural networks capable of processing highly complex information such as radiographic images and three-dimensional datasets [8].

Current research in implant dentistry increasingly investigates machine learning applications for implant survival prediction, peri-implant bone loss estimation, radiographic interpretation, implant planning, surgical guidance, prosthetic risk assessment, complication prediction, and personalized treatment optimization [9].

Despite rapidly growing interest, important limitations remain regarding dataset quality, external validation, interpretability, ethical considerations, and integration into routine clinical workflows [10].

This chapter reviews the principles of machine learning, predictive analytics, implant prognostic variables, clinical applications, radiographic analysis, peri-implantitis prediction, complication forecasting, digital implant workflows, limitations, ethical concerns, and future perspectives regarding machine learning in implant dentistry.

Fundamentals of Machine Learning

Machine learning refers to computational algorithms capable of identifying patterns and learning relationships from datasets without being explicitly programmed for every individual decision [11]. Unlike conventional software systems that follow predefined rules, machine learning algorithms improve predictive performance through iterative exposure to larger datasets and optimization processes [12].

Machine learning models generally require structured input data, training datasets, validation datasets, and measurable predictive outputs [13]. Clinical datasets used in implant dentistry may include demographic information, systemic diseases, smoking history, periodontal status, radiographic parameters, implant dimensions, prosthetic variables, surgical protocols, and follow-up outcomes [14].

Supervised learning represents one of the most commonly used machine learning approaches in healthcare applications [15]. In supervised learning, algorithms are trained using labeled datasets in which both input variables and known outcomes are provided. Examples in implant dentistry include prediction of implant survival, marginal bone loss, peri-implantitis occurrence, and prosthetic complications [16]. Common supervised learning algorithms include logistic regression, decision trees, random forest models, support vector machines, gradient boosting algorithms, and artificial neural networks [17].

Unsupervised learning analyzes unlabeled data and attempts to identify hidden structures, clustering patterns, or previously unrecognized relationships [18]. This approach may potentially identify subgroups of implant patients with similar biological or behavioral risk profiles.

Deep learning represents a specialized subset of machine learning involving multilayer artificial neural networks [19]. Deep learning systems are particularly powerful in image analysis because they may automatically identify highly complex visual features. Convolutional neural networks are among the most widely used deep learning architectures in dental imaging and CBCT interpretation [20].

Reinforcement learning involves computational systems learning through feedback-based optimization processes [21]. Although currently less common in implant dentistry, reinforcement learning may eventually contribute to robotic implant surgery and adaptive treatment planning systems.

Understanding the fundamental principles of machine learning is essential for appropriate interpretation and responsible clinical application of predictive technologies in implant dentistry.

Predictive Analytics in Healthcare and Dentistry

Predictive analytics combines statistical modeling, machine learning, and data mining techniques to estimate future outcomes based on historical and real-time information [22]. Healthcare systems increasingly utilize predictive analytics for disease risk estimation, personalized treatment planning, complication prevention, resource management, and prognostic assessment [23].

In dentistry, predictive analytics has expanded rapidly because of widespread digitalization and increased availability of large clinical datasets [24]. Electronic health records, digital radiography, CBCT imaging, intraoral scanning, and CAD/CAM systems generate substantial quantities of structured clinical data suitable for computational analysis [25].

Traditional evidence-based implant dentistry generally relies on population-level statistics derived from clinical studies and systematic reviews [26]. However, individual patients often demonstrate significant biological variability that may not be fully addressed by conventional approaches.

Predictive analytics may therefore help clinicians move toward more personalized implant treatment planning by integrating multiple variables simultaneously [27]. Machine learning systems may analyze relationships among systemic diseases, smoking habits, periodontal history, oral hygiene, implant geometry, occlusal loading, bone density, prosthetic design, and radiographic features to estimate individualized prognosis [28].

The integration of predictive analytics into implant dentistry may improve treatment predictability, reduce complication risk, optimize surgical planning, facilitate patient communication, and support long-term maintenance strategies [29]. As computational technologies continue to evolve, predictive analytics is expected to play an increasingly important role in precision implant dentistry.

Prognostic Factors Influencing Implant Outcomes

Successful machine learning models in implant dentistry depend heavily on accurate identification and integration of prognostic variables associated with implant survival and complications [30]. Implant outcomes are multifactorial and influenced by patient-related, surgical, prosthetic, biomechanical, and maintenance-related factors.

Systemic diseases represent important variables in predictive implant models. Diabetes mellitus has been associated with impaired osseointegration, delayed wound healing, and increased peri-implant inflammation, particularly in poorly controlled patients [31]. Osteoporosis, cardiovascular disease, autoimmune disorders, immunosuppression, and metabolic conditions may additionally influence implant prognosis [32].

Smoking remains one of the most consistently identified risk factors associated with implant failure and peri-implantitis [33]. Tobacco use negatively affects vascularization, immune response, soft tissue healing, and bone metabolism. Machine learning systems frequently identify smoking history as a major contributor to predictive risk stratification models.

History of periodontitis is another important prognostic variable because patients with previous periodontal destruction demonstrate increased susceptibility to peri-implant bone loss and inflammatory complications [34]. Poor plaque control and inadequate supportive maintenance further increase long-term complication risk.

Bone-related variables also play critical roles in implant success prediction. Bone density, cortical thickness, trabecular structure, and residual ridge morphology significantly influence primary implant stability and osseointegration [35]. CBCT-derived radiographic measurements are increasingly incorporated into machine learning models to improve predictive accuracy.

Surgical factors including implant position, insertion torque, drilling protocols, flap design, surgical experience, and thermal trauma additionally influence implant outcomes [36]. Digital guided surgery systems may reduce positioning errors and improve surgical precision.

Prosthetic variables such as occlusal loading, cantilever length, prosthetic fit, crown-to-implant ratio, and prosthetic material selection are also important determinants of long-term implant stability [37]. Excessive biomechanical stress may contribute to screw loosening, prosthetic fracture, crestal bone loss, and implant overload.

Behavioral and maintenance-related factors including oral hygiene, compliance with supportive care, parafunctional habits, and frequency of professional follow-up significantly influence long-term implant survival [38].

Machine learning models capable of simultaneously integrating these complex variables may potentially provide more individualized and accurate prognostic assessments than traditional statistical approaches alone.

Machine Learning Models for Implant Survival Prediction

Prediction of implant survival represents one of the most extensively investigated applications of machine learning in implant dentistry [39]. Conventional survival analyses such as Kaplan-

Meier methods and Cox proportional hazards models remain valuable tools; however, machine learning algorithms may better capture nonlinear interactions among multiple prognostic variables.

Random forest algorithms have demonstrated promising predictive performance because they combine multiple decision trees and reduce overfitting risk while improving classification accuracy [40]. These systems may effectively analyze large multidimensional clinical datasets and identify influential prognostic factors associated with implant success or failure.

Support vector machines are another commonly investigated machine learning technique capable of separating complex datasets into predictive categories using multidimensional decision boundaries [41]. Several studies have reported favorable accuracy in prediction of implant survival and peri-implant disease using support vector machine models.

Artificial neural networks are particularly valuable for processing highly complex biological and radiographic data [42]. These systems are inspired by human neural architecture and may continuously optimize predictive performance through iterative learning processes.

Deep learning algorithms have demonstrated increasing utility in interpretation of radiographic images and CBCT datasets [43]. Convolutional neural networks may automatically recognize radiographic features associated with implant positioning, marginal bone changes, peri-implant radiolucencies, and anatomical limitations.

Several retrospective clinical studies have reported encouraging predictive performance for machine learning-based implant survival models [44]. Predictive variables commonly incorporated into these systems include smoking status, systemic diseases, implant dimensions, bone quality, insertion torque, periodontal history, oral hygiene parameters, and prosthetic characteristics.

Machine learning systems may additionally assist clinicians in identifying high-risk patients before treatment initiation, thereby allowing modification of surgical protocols, maintenance schedules, or prosthetic designs [45].

Despite promising results, many currently available studies remain limited by relatively small datasets, retrospective methodologies, short follow-up periods, and lack of external multicenter

validation [46]. Generalizability therefore remains one of the most important challenges before widespread clinical implementation can occur.

Prediction of Marginal Bone Loss

Marginal bone loss represents one of the most important biological indicators of implant health and long-term stability [47]. Excessive crestal bone resorption may compromise osseointegration, soft tissue support, aesthetics, and implant survival.

Machine learning systems are increasingly investigated for prediction of marginal bone loss because numerous variables contribute simultaneously to peri-implant bone remodeling [48].

Radiographic analysis plays a central role in these predictive models. Digital periapical radiographs and CBCT imaging provide quantitative measurements regarding crestal bone levels, cortical thickness, trabecular density, and peri-implant morphology [49].

Deep learning algorithms may automatically identify radiographic bone changes and detect early peri-implant deterioration before clinically evident disease develops [50].

Patient-related variables including smoking, diabetes mellitus, oral hygiene, and periodontal history are frequently integrated into predictive models evaluating marginal bone loss risk [51].

Surgical and prosthetic variables such as implant-abutment connection type, implant diameter, implant depth, occlusal loading, prosthetic fit, and cantilever forces additionally influence crestal bone remodeling [52].

Several machine learning studies have demonstrated higher predictive accuracy for marginal bone loss estimation compared with conventional regression analyses [53]. These findings suggest substantial potential for personalized implant maintenance strategies and earlier intervention protocols.

Early prediction of progressive bone loss may facilitate preventive measures including reinforcement of oral hygiene, occlusal adjustment, supportive periodontal therapy, or modification of prosthetic loading conditions [54].

As longitudinal datasets continue expanding, predictive systems for marginal bone loss are expected to become increasingly accurate and clinically useful.

Machine Learning in Peri-Implantitis Prediction

Peri-implantitis is one of the most significant biological complications associated with implant therapy and represents a major cause of late implant failure [55]. The disease is characterized by inflammatory destruction of peri-implant soft tissues accompanied by progressive supporting bone loss.

The multifactorial nature of peri-implantitis makes it particularly suitable for machine learning-based predictive analysis because disease progression depends on complex interactions among microbial, immunological, systemic, prosthetic, and behavioral factors [56].

Traditional diagnostic methods for peri-implantitis primarily rely on clinical probing, bleeding on probing, suppuration, radiographic bone loss evaluation, and patient history [57]. However, these methods generally identify disease after tissue destruction has already occurred.

Machine learning systems may potentially allow earlier identification of high-risk patients by analyzing large datasets containing clinical, radiographic, microbiological, and behavioral information [58].

Predictive variables commonly associated with peri-implantitis include smoking history, poor plaque control, previous periodontitis, uncontrolled diabetes mellitus, inadequate maintenance therapy, excess cement, prosthetic design, implant surface characteristics, and biomechanical overload [59].

Several machine learning models have demonstrated promising predictive accuracy for peri-implant disease risk stratification [60]. Random forest and support vector machine algorithms appear particularly effective in identifying complex nonlinear relationships among multiple peri-implant risk variables.

Deep learning systems may additionally analyze radiographic images to identify subtle peri-implant bone changes associated with early inflammatory disease [61]. Automated radiographic interpretation may therefore improve diagnostic consistency and facilitate earlier intervention.

Microbiological and salivary biomarker analysis also represent emerging areas in machine learning-assisted peri-implantitis prediction [62]. Computational models integrating

inflammatory cytokines, bacterial profiles, and host immune markers may potentially improve individualized disease prediction.

Predictive systems for peri-implantitis may support development of personalized maintenance schedules and preventive protocols tailored to patient-specific risk profiles [63].

Despite encouraging research findings, standardization of diagnostic criteria and multicenter validation remain necessary before widespread routine implementation can occur [64].

Radiographic Applications of Machine Learning in Implant Dentistry

Radiographic interpretation represents one of the most rapidly developing applications of machine learning in implant dentistry [65]. The increasing availability of digital imaging datasets has substantially accelerated development of deep learning systems for dental radiology.

Convolutional neural networks are particularly effective for image recognition tasks because they automatically extract complex hierarchical visual features from radiographic images [66].

In implant dentistry, machine learning systems may assist clinicians in anatomical landmark identification, implant planning, bone density analysis, implant positioning assessment, and postoperative complication detection [67].

Automated detection of the mandibular canal, maxillary sinus boundaries, mental foramen, and adjacent tooth roots may improve surgical safety during implant planning [68].

Several studies have demonstrated high accuracy rates for deep learning models in identifying anatomical structures on CBCT images [69].

Machine learning systems may additionally assist in evaluation of bone quality and trabecular architecture prior to implant placement [70]. Automated bone density analysis may improve estimation of primary implant stability and osseointegration potential.

Radiographic prediction of implant stability is another emerging field. Computational analysis of peri-implant bone patterns may potentially correlate with insertion torque values and implant stability quotient measurements [71].

Deep learning models are also increasingly investigated for automated detection of peri-implant bone loss, peri-implant radiolucencies, implant fractures, prosthetic misfit, and other complications [72].

Automated radiographic interpretation may improve diagnostic consistency, reduce observer variability, and decrease clinical workload [73].

Nevertheless, image quality variation, limited dataset diversity, and insufficient external validation remain important limitations in current radiographic machine learning research [74].

Machine Learning and Digital Implant Workflows

The increasing digitalization of implant dentistry has created substantial opportunities for integration of machine learning technologies into routine clinical workflows [75].

Digital implant workflows commonly involve intraoral scanning, CBCT imaging, virtual treatment planning, guided surgery, CAD/CAM prosthetics, and digital follow-up systems [76].

Machine learning algorithms may potentially optimize multiple phases of these workflows through automated analysis and predictive modeling.

Virtual implant planning systems increasingly incorporate artificial intelligence-assisted recommendations regarding implant size, angulation, positioning, and prosthetic emergence profiles [77].

Machine learning-based planning systems may analyze anatomical limitations, prosthetic requirements, bone availability, and biomechanical conditions simultaneously to generate individualized treatment suggestions.

Digital surgical guides generated through AI-assisted workflows may improve implant positioning accuracy and reduce operative variability [78].

Machine learning may additionally contribute to robotic implant surgery systems capable of improving precision and minimizing human error [79].

Predictive maintenance systems integrating clinical and radiographic follow-up data may also help identify implants at increased risk for biological or mechanical complications [80].

The integration of machine learning into digital implant workflows may improve efficiency, standardization, surgical precision, and personalized patient care.

However, successful integration requires interoperability among imaging systems, planning software, electronic health records, and machine learning platforms [81].

Ethical Considerations and Limitations

Despite substantial potential, machine learning applications in implant dentistry raise important ethical, legal, and practical concerns [82].

One of the major limitations involves dataset quality. Machine learning systems are highly dependent on the quality, quantity, and diversity of training data [83]. Incomplete, biased, or poorly standardized datasets may produce inaccurate or unreliable predictions.

Generalizability also represents a significant challenge because many published machine learning studies utilize relatively small retrospective datasets from single institutions [84].

External multicenter validation is therefore essential before predictive models may be safely generalized to broader populations.

Interpretability is another important concern. Complex deep learning models often function as “black box” systems in which internal decision-making processes remain difficult to explain [85].

Clinicians may therefore hesitate to rely on predictions generated by systems lacking transparent reasoning pathways.

Patient privacy and data security additionally represent major ethical concerns because machine learning systems frequently require large quantities of sensitive clinical information [86].

Regulatory approval and medicolegal responsibility remain incompletely defined in many jurisdictions. Questions regarding liability for incorrect AI-assisted clinical decisions continue to generate debate [87].

Importantly, machine learning systems should not replace clinical judgment. These technologies are best viewed as decision-support tools designed to assist rather than replace experienced clinicians [88].

Careful ethical regulation, transparent validation, and clinician education will therefore remain essential as predictive technologies continue to evolve.

Future Perspectives

Machine learning and predictive analytics are expected to play increasingly important roles in the future of implant dentistry as digital technologies and clinical databases continue to expand [89]. The integration of artificial intelligence-assisted systems into routine implant workflows may substantially improve diagnostic accuracy, treatment predictability, and personalized patient care.

Future predictive systems will likely incorporate multidimensional datasets including radiographic imaging, genetic information, salivary biomarkers, microbiological profiles, systemic health parameters, occlusal analysis, and real-time maintenance data [90]. Such comprehensive integration may permit highly individualized risk assessment and precision implant therapy.

Deep learning algorithms are expected to become increasingly sophisticated in radiographic interpretation and three-dimensional image analysis [91]. Automated identification of anatomical structures, prediction of bone quality, and early detection of peri-implant disease may eventually become routine components of digital implant planning systems.

Artificial intelligence-assisted surgical navigation and robotic implant placement technologies may additionally improve surgical precision and reduce operator-dependent variability [92]. These systems may help optimize implant positioning, minimize anatomical complications, and improve prosthetically driven treatment planning.

Predictive maintenance systems capable of continuously analyzing longitudinal patient data may also facilitate earlier intervention before significant biological or prosthetic complications occur [93]. Personalized recall intervals and preventive strategies based on machine learning risk assessment models may improve long-term implant survival.

Another important future direction involves integration of wearable technologies and remote monitoring systems into implant maintenance protocols [94]. Continuous collection of patient-related behavioral and physiological data may further improve predictive accuracy.

Despite these promising developments, successful clinical integration will require large multicenter datasets, external validation studies, transparent algorithms, ethical regulation, and clinician education [95]. Standardization of data collection and reporting protocols will also remain essential for development of reliable predictive systems.

Future implant dentistry is therefore expected to move progressively toward data-driven, personalized, and precision-oriented clinical care supported by machine learning technologies.

Conclusion

Machine learning and predictive analytics represent rapidly evolving technologies with substantial potential to transform implant dentistry. Implant treatment outcomes depend on complex interactions among biological, surgical, prosthetic, biomechanical, and behavioral variables that are often difficult to evaluate comprehensively through conventional clinical approaches alone.

Machine learning algorithms may analyze large multidimensional datasets and identify predictive relationships associated with implant survival, marginal bone loss, peri-implantitis, prosthetic complications, and long-term treatment prognosis. Deep learning systems additionally demonstrate significant potential in radiographic interpretation, digital implant planning, and automated complication detection.

The integration of predictive analytics into implant dentistry may improve treatment predictability, facilitate individualized risk assessment, optimize surgical planning, support preventive maintenance strategies, and enhance patient communication.

Current evidence regarding machine learning applications in implant dentistry remains highly promising; however, important limitations continue to exist regarding dataset quality, external validation, interpretability, ethical concerns, and routine clinical implementation.

Machine learning systems should currently be viewed primarily as clinical decision-support tools rather than replacements for professional expertise and clinical judgment.

Future developments involving large-scale clinical databases, advanced imaging technologies, biomarker integration, robotic surgery, and precision medicine are expected to further expand the role of predictive analytics in implant dentistry.

Overall, machine learning and predictive analytics are likely to become increasingly integrated into modern implant practice and may contribute substantially to safer, more personalized, and more predictable implant treatment outcomes.

References

- Brånemark PI, Zarb GA, Albrektsson T. Tissue-Integrated Prostheses. Quintessence Publishing; 1985.
- Albrektsson T, Zarb G, Worthington P, Eriksson AR. Long-term efficacy of dental implants. *Int J Oral Maxillofac Implants*. 1986;1:11-25.
- Esposito M, Hirsch JM, Lekholm U, Thomsen P. Biological factors contributing to implant failures. *Eur J Oral Sci*. 1998;106:721-764.
- Jordan MI, Mitchell TM. Machine learning: trends and perspectives. *Science*. 2015;349:255-260.
- Deo RC. Machine learning in medicine. *Circulation*. 2015;132:1920-1930.
- Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry. *J Dent Res*. 2020;99:769-774.
- Russell S, Norvig P. *Artificial Intelligence: A Modern Approach*. Pearson; 2021.
- LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521:436-444.
- Hung K, Montalvao C, Tanaka R, Kawai T, Bornstein MM. The use and performance of artificial intelligence applications in dental and maxillofacial radiology. *Dentomaxillofac Radiol*. 2020;49:20190107.
- Beam AL, Kohane IS. Big data and machine learning in health care. *JAMA*. 2018;319:1317-1318.
- Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25:44-56.
- Mitchell TM. *Machine Learning*. McGraw Hill; 1997.
- Goodfellow I, Bengio Y, Courville A. *Deep Learning*. MIT Press; 2016.
- Rokach L, Maimon O. *Data Mining with Decision Trees*. World Scientific; 2015.
- Kotsiantis SB. Supervised machine learning: a review. *Informatica*. 2007;31:249-268.

- Bishop CM. Pattern Recognition and Machine Learning. Springer; 2006.
- Breiman L. Random forests. Mach Learn. 2001;45:5-32.
- Jain AK. Data clustering: 50 years beyond k-means. Pattern Recognit Lett. 2010;31:651-666.
- Schmidhuber J. Deep learning in neural networks. Neural Netw. 2015;61:85-117.
- Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 2012;25:1097-1105.
- Sutton RS, Barto AG. Reinforcement Learning: An Introduction. MIT Press; 2018.
- Shmueli G, Koppius OR. Predictive analytics in information systems research. MIS Q. 2011;35:553-572.
- Obermeyer Z, Emanuel EJ. Predicting the future in medicine. N Engl J Med. 2016;375:1216-1219.
- Khanagar SB, Al-Ehaideb A, Vishwanathaiah S, Maganur PC, Patil S, Baeshen HA, et al. Developments, application, and performance of AI in dentistry. J Dent Sci. 2021;16:508-522.
- Rekow ED. Digital dentistry: the new state of the art. J Am Dent Assoc. 2020;151:229-231.
- Buser D, Sennerby L, De Bruyn H. Modern implant dentistry based on osseointegration. Periodontol 2000. 2017;73:7-21.
- Chrcanovic BR, Kisch J, Albrektsson T, Wennerberg A. Factors influencing implant failure. Clin Implant Dent Relat Res. 2018;20:44-53.
- Derks J, Tomasi C. Peri-implant health and disease. J Clin Periodontol. 2015;42:S158-S171.
- Lang NP, Berglundh T. Periimplant diseases. J Clin Periodontol. 2011;38:178-181.
- Moy PK, Medina D, Shetty V, Aghaloo TL. Dental implant failure rates and associated risk factors. Int J Oral Maxillofac Implants. 2005;20:569-577.
- Javed F, Romanos GE. Impact of diabetes mellitus and glycemic control on implant therapy. Clin Oral Implants Res. 2009;20:171-180.

- Bornstein MM, Cionca N, Mombelli A. Systemic conditions and implant therapy. *Int J Oral Maxillofac Implants*. 2009;24:12-27.
- Bain CA, Moy PK. The association between smoking and implant failure. *Int J Oral Maxillofac Implants*. 1993;8:609-615.
- Karoussis IK, Salvi GE, Heitz-Mayfield LJA, Brägger U, Hämmerle CHF, Lang NP. Long-term implant prognosis in patients with periodontitis. *Clin Oral Implants Res*. 2003;14:329-339.
- Lekholm U, Zarb GA. Patient selection and preparation. In: *Tissue-Integrated Prostheses*. Quintessence Publishing; 1985.
- Misch CE. *Contemporary Implant Dentistry*. 3rd ed. Mosby Elsevier; 2008.
- Rangert B, Krogh PH, Langer B, Van Roekel N. Bending overload and implant fracture. *Int J Oral Maxillofac Implants*. 1995;10:326-334.
- Lindhe J, Meyle J. Peri-implant diseases and maintenance. *J Clin Periodontol*. 2008;35:282-285.
- Albrektsson T, Donos N. Implant survival and complications. *Periodontol 2000*. 2012;60:152-160.
- Breiman L. Random forests. *Mach Learn*. 2001;45:5-32.
- Cortes C, Vapnik V. Support-vector networks. *Mach Learn*. 1995;20:273-297.
- Haykin S. *Neural Networks and Learning Machines*. Pearson; 2009.
- Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. Deep learning in medical image analysis. *Med Image Anal*. 2017;42:60-88.
- Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based CNN algorithm. *J Dent*. 2018;77:106-111.
- Choi HI, Jung SK, Baek SH, Lim WH, Ahn SJ, Yang IH, et al. Artificial intelligence for implant planning. *J Clin Med*. 2021;10:555.
- Senders JT, Staples PC, Karhade AV, Zaki MM, Gormley WB, Broekman MLD, et al. Machine learning and neurosurgical outcome prediction. *World Neurosurg*. 2018;109:476-486.

- Canullo L, Penarrocha D, Clementini M, Iannello G, Micarelli C. Marginal bone loss around implants. *Int J Prosthodont*. 2015;28:457-464.
- Monje A, Insua A, Wang HL. Understanding peri-implant bone loss. *J Periodontol*. 2019;90:258-271.
- Schwarz F, Derks J, Monje A, Wang HL. Peri-implantitis. *J Clin Periodontol*. 2018;45:S246-S266.
- Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, et al. Deep learning for radiographic bone loss detection. *J Clin Periodontol*. 2019;46:482-490.
- Heitz-Mayfield LJA. Peri-implant diseases: diagnosis and risk indicators. *J Clin Periodontol*. 2008;35:292-304.
- Qian J, Wennerberg A, Albrektsson T. Reasons for marginal bone loss around implants. *Clin Implant Dent Relat Res*. 2012;14:792-807.
- Cha JY, Lee JH, Kim HJ, Shin K, Hwang CJ. Prediction of implant outcomes using machine learning. *Comput Methods Programs Biomed*. 2021;196:105707.
- Ramanauskaite A, Tervonen T. Detection of peri-implant diseases. *Clin Oral Implants Res*. 2016;27:124-134.
- Berglundh T, Armitage G, Araujo MG, Avila-Ortiz G, Blanco J, Camargo PM, et al. Peri-implant diseases and conditions. *J Clin Periodontol*. 2018;45:S286-S291.
- Derks J, Schaller D, Håkansson J, Wennström JL, Tomasi C, Berglundh T. Effectiveness of implant therapy analyzed in a Swedish population. *J Dent Res*. 2016;95:43-49.
- Renvert S, Polyzois I. Clinical approaches to peri-implant mucositis and peri-implantitis. *Periodontol 2000*. 2015;68:369-404.
- Rokn A, Aslroosta H, Akbari S, Najafi H, Zayeri F, Hashemi K. Machine learning in peri-implantitis prediction. *Clin Exp Dent Res*. 2020;6:558-564.
- Heitz-Mayfield LJA, Salvi GE. Peri-implant mucositis and peri-implantitis. *J Clin Periodontol*. 2018;45:S237-S245.

- Shibli JA, Ferrari DS, Siroma RS, Figueiredo LC, Faveri M, Feres M. Microbiological and immunological predictive factors in peri-implant disease. *Clin Oral Implants Res.* 2008;19:789-798.
- Lee CT, Huang YW, Zhu L, Weltman R. Prevalences of peri-implantitis and peri-implant mucositis. *J Dent.* 2017;62:1-12.
- Belibasakis GN. Microbiological and immuno-pathological aspects of peri-implant diseases. *Arch Oral Biol.* 2014;59:66-72.
- Lang NP, Tonetti MS. Periodontal risk assessment and supportive care. *Oral Health Prev Dent.* 2003;1:7-16.
- Sanz M, Chapple IL. Clinical research on peri-implant diseases. *J Clin Periodontol.* 2012;39:202-206.
- Hung M, Voss MW, Rosales MN, Li W, Su W, Xu J, et al. Application of machine learning in dental imaging. *Oral Surg Oral Med Oral Pathol Oral Radiol.* 2020;129:398-404.
- LeCun Y, Bengio Y. Convolutional networks for images and speech. *Nature.* 1998;393:245-248.
- Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. AI for CBCT interpretation in implant dentistry. *Oral Radiol.* 2020;36:353-364.
- Kwak GH, Kwak EJ, Song JM, Park HR, Jung YH, Cho BH, et al. Automatic mandibular canal detection using deep learning. *Dentomaxillofac Radiol.* 2020;49:20190307.
- Setzer FC, Shi KJ, Zhang Z, Yan H, Yoon H, Mupparapu M, et al. Artificial intelligence in dental radiography. *J Endod.* 2020;46:987-993.
- Lindh C, Obrant K, Petersson A. Bone density and implant stability. *Clin Oral Implants Res.* 1996;7:108-113.
- Meredith N. Assessment of implant stability as a prognostic determinant. *Int J Prosthodont.* 1998;11:491-501.
- Bayrakdar IS, Orhan K, Odabas A, Aslan AF, Bilgir E, Ezhov M. Deep learning for detection of dental implant systems. *Clin Oral Investig.* 2021;25:5269-5277.

- Ariji Y, Fukuda M, Kise Y, Nozawa M, Yanashita Y, Fujita H, et al. CNN for dental radiographic interpretation. *Oral Radiol.* 2019;35:9-14.
- Schwendicke F, Golla T, Dreher M, Krois J. Convolutional neural networks in dental diagnostics. *J Dent.* 2019;91:103226.
- Mangano FG, Admakin O. Artificial intelligence and digital dentistry. *J Dent.* 2020;91:103223.
- Joda T, Gallucci GO. Digital technology in implant prosthodontics. *Int J Prosthodont.* 2015;28:117-119.
- Block MS, Emery RW. Static and dynamic guided implant surgery. *J Oral Maxillofac Surg.* 2016;74:1515.e1-1515.e21.
- D'haese J, Ackhurst J, Wismeijer D, De Bruyn H, Tahmaseb A. Current state of guided implant surgery. *Clin Oral Implants Res.* 2017;28:88-95.
- Block MS, Altman A. Robotic-guided dental implant surgery. *J Oral Maxillofac Surg.* 2021;79:1139-1146.
- Papi P, Di Carlo S, Rosella D, De Angelis F, Pompa G. Digital technologies and implant maintenance. *Oral Implantol.* 2017;10:263-272.
- Rekow ED. Digital dentistry: integrating technologies for clinical care. *Compend Contin Educ Dent.* 2013;34:644-650.
- Char DS, Shah NH, Magnus D. Implementing machine learning in healthcare. *N Engl J Med.* 2018;378:981-983.
- Wiens J, Shenoy ES. Machine learning for healthcare. *Circ Cardiovasc Qual Outcomes.* 2018;11:e004493.
- Liu Y, Chen PC, Krause J, Peng L. How to read articles about machine learning. *JAMA.* 2019;322:1806-1816.
- Castelvecchi D. Can we open the black box of AI? *Nature.* 2016;538:20-23.
- Price WN, Cohen IG. Privacy in the age of medical big data. *Nat Med.* 2019;25:37-43.

- Gerke S, Minssen T, Cohen G. Ethical and legal challenges of AI-driven healthcare. *Artif Intell Healthc.* 2020;295-336.
- Topol EJ. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again.* Basic Books; 2019.
- Davenport T, Kalakota R. The potential for AI in healthcare. *Future Healthc J.* 2019;6:94-98.
- Mirnezami R, Nicholson J, Darzi A. Preparing for precision medicine. *N Engl J Med.* 2012;366:489-491.
- Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Deep neural networks in medical diagnosis. *Nature.* 2017;542:115-118.
- Yang Y, Lv Z, Li Y. Robotics and AI in surgery. *Comput Methods Programs Biomed.* 2021;208:106179.
- Obermeyer Z, Lee TH. Lost in thought — the limits of AI. *N Engl J Med.* 2017;377:1209-1211.
- Patel S, Durack C, Abella F, Shemesh H, Roig M, Lemberg K. Cone beam CT in endodontics and implant dentistry. *Int Endod J.* 2015;48:3-15.
- Collins GS, Moons KGM. Reporting AI prediction models. *BMJ.* 2019;365:l1286.

CHAPTER 4

DIGITAL FABRICATION OF PROVISIONAL RESTORATIONS IN FIXED PROSTHODONTICS: MATERIALS, TECHNOLOGIES, AND CLINICAL DECISION-MAKING

Beşar İZZETAĞA¹ , Duygu Ece KESKİN²

¹ Dr. Öğr. Üyesi, Karabük Üniversitesi, Diş Hekimliği Fakültesi, Protetik Diş Tedavisi Anabilim Dalı, ORCID: 0000-0001-7075-2265

² Dr. Öğr. Üyesi, Karabük Üniversitesi, Diş Hekimliği Fakültesi, Protetik Diş Tedavisi Anabilim Dalı, ORCID: 0000-0002-8906-1760

1. Introduction

A provisional restoration does far more than occupy the space of a prepared tooth. During the interval between preparation and delivery of the definitive prosthesis it protects the abutment from thermal, chemical, and mechanical insults, supports periodontal health, maintains occlusal and positional stability, and allows both clinician and patient to evaluate esthetics and function before irreversible decisions are made (Burns et al., 2003; Rosenstiel et al., 2022).

Marginal fit deserves particular attention in this context. Poor adaptation at the margin encourages plaque retention and disrupts the subgingival microbiota, which can trigger gingival inflammation and complicate the remaining steps of treatment (Khng et al., 2016; Al Wadei et al., 2022). Achieving a consistently accurate margin is therefore not merely a technical goal but a biological necessity.

Chairside fabrication with self-curing Polymethyl methacrylate (PMMA) or bisphenol A-glycidyl methacrylate-based (bis-acryl) composite resins has long been the standard approach, yet these materials carry inherent limitations: polymerization shrinkage, exothermic setting reactions, porosity, and variable marginal accuracy among them (Astudillo-Rubio et al., 2018; Mohajeri et al., 2021). The heat generated during PMMA polymerization can damage soft tissue and produce odour, contributing to patient discomfort (Rayyan et al., 2015). The adoption of CAD/CAM technology has opened a more controlled path, with milled and printed provisional restorations demonstrating measurably better mechanical and marginal properties in recent literature (Jain et al., 2022; Valenti et al., 2024; Rexhepi et al., 2023).

This chapter examines the two digital fabrication routes available for provisional restorations subtractive and additive manufacturing and the individual technologies within each. It reviews the comparative evidence on mechanical behaviour, marginal accuracy, esthetics, wear, biocompatibility, cementation, and repair, and closes with a framework for selecting between approaches according to clinical indication.

2. Digital Fabrication Technologies

Digital production of provisional restorations follows one of two fundamentally different routes. Subtractive manufacturing removes material from a prepolymerized block until the designed geometry remains, whereas additive manufacturing builds the restoration incrementally from a liquid or filament precursor. Both begin with the same digital dataset,

but the physical and mechanical characteristics of the resulting restoration diverge considerably depending on which route is taken (Jain et al., 2022; Rexhepi et al., 2023).

2.1 Subtractive Manufacturing (CAD/CAM Milling)

In milling the restoration is cut from a monolithic block or disc using rotary instruments under computer control (Chavali et al., 2017). The decisive advantage of this approach lies not in the machining itself but in the raw material: PMMA blocks are industrially polymerized under high temperature and pressure, producing a highly cross-linked network with minimal residual monomer and virtually no internal porosity (Rexhepi et al., 2023; Berghaus et al., 2023). Conventional chairside polymerization cannot replicate these conditions, which explains the persistent gap between the two approaches (Astudillo-Rubio et al., 2018).

Milled PMMA outperforms conventionally polymerized acrylic in hardness, flexural strength, flexural modulus, and impact resistance (Rexhepi et al., 2023; Mangtani et al., 2025). In an early comparison of fabrication methods, maximum fracture loads of provisional crowns ranged from 711.09 to 1392.1 N; among PMMA-based materials the CAD/CAM-milled group recorded the highest value at 959.59 N, while composite-based materials showed significantly higher fracture strength than PMMA-based ones (Karaokutan et al., 2015). Three-unit milled frameworks tolerate loads well beyond physiological masticatory forces (Abad-Coronel et al., 2023; Henderson et al., 2022), and restorations intended for up to twelve months of function are now routinely produced by milling (Rexhepi et al., 2023).

Beyond PMMA, several polymer systems are available in block or disc form (**Table 1**).

Table 1. Mean fracture load of milled polymer systems for three-unit interim fixed dental prostheses.

Material	Mean fracture load (N)
PMMA	1302.71
Acetal resin	1796.20
Graphene-reinforced PMMA	1990.02
Polysulfone	2234.97

Source: Data from Abad-Coronel et al. (2023). Values derive from a single in vitro loading protocol and are not directly comparable with other studies.

All four materials exceeded physiological masticatory loads, but the alternative polymers withstood substantially higher loads than PMMA in the same configuration (Abad-Coronel et al., 2023). For long-span provisionals, where a mid-treatment fracture carries significant clinical cost, this margin may be relevant, although clinical documentation of these materials remains limited compared with PMMA.

The principal limitations of milling are material waste, bur wear, and the restriction imposed by block dimensions on span length. Fine internal geometries and sharp line angles are also difficult to reproduce, because machining accuracy is bounded by the diameter of the smallest available bur (Chavali et al., 2017).

2.2 Additive Manufacturing (3D Printing)

Additive manufacturing constructs the restoration layer by layer from a photopolymerizable resin or a thermoplastic filament. Material consumption is limited to what forms the object and its supports, complex internal geometries pose no difficulty, and several restorations can be produced simultaneously on a single build platform (Liang et al., 2025). The clinical workflow becomes correspondingly flexible: a tooth can be prepared, scanned, and the printing job started while the clinician attends to other procedures.

Not all printing technologies are equally suited to provisional restorations. Differences in light source, curing mechanism, and layer resolution translate directly into differences in mechanical behaviour and surface quality (Yıldırım et al., 2025).

The technologies relevant to provisional restorations fall into two groups by mechanism: vat photopolymerization systems, which cure liquid resin with light stereolithography (SLA), digital light processing (DLP), and liquid crystal display (LCD) and material extrusion, represented by fused deposition modeling (FDM).

2.2.1 Stereolithography (SLA)

SLA is the oldest and still one of the most widely used vat photopolymerization methods in dentistry. A focused ultraviolet laser traces the cross-section of each layer across the surface of a liquid resin vat, polymerizing the resin point by point before the platform shifts (Liang et al., 2025). Because the laser spot can be focused to a very small diameter, SLA achieves excellent resolution and reproduces clear marginal detail reliably; printed interim restorations have shown clinically acceptable marginal and internal fit (Alharbi et al., 2018).

The trade-off is speed, and the mechanical properties of SLA resins vary considerably between commercial products. A systematic review found that some SLA resins showed significantly lower flexural strength and hardness than milled PMMA and bis-acrylic resins, while others delivered clinically acceptable marginal adaptation, surface roughness, and fracture strength; the authors concluded that this inconsistency, rather than any intrinsic limitation of the technology, is the main obstacle to predictable clinical performance and called for standardization of protocols (Danila et al., 2025).

2.2.2 Digital Light Processing (DLP)

DLP replaces the tracing laser with a digital micromirror device that projects the entire cross-sectional image onto the resin surface in a single exposure, so each layer cures in one step regardless of its geometric complexity (Liang et al., 2025). In three-unit fixed dental prostheses, DLP and SLA both produced significantly higher flexural strength than conventional fabrication, with no significant difference between the two printing methods (Park et al., 2020). A network meta-analysis covering DLP, SLA, LCD, selective laser sintering (SLS), digital light synthesis (DLS), and FDM systems reached a comparable conclusion regarding the two dominant vat photopolymerization approaches (Yıldırım et al., 2025).

The characteristic limitation of DLP arises from its projection geometry: resolution is determined by pixel size and projection area, so enlarging the build area at fixed projector resolution coarsens the detail. Layer thickness itself has been shown to influence the trueness of printed interim prostheses (Çakmak et al., 2024).

2.2.3 Liquid Crystal Display (LCD)

LCD printing, sometimes described as masked stereolithography, uses an array of ultraviolet light-emitting diodes behind a liquid crystal panel acting as a dynamic mask, so the full layer cures simultaneously (Yıldırım et al., 2025). The absence of a laser assembly or projection optics makes these devices considerably cheaper, which has driven rapid uptake in smaller practices and laboratories. Resolution is fixed by the panel's native pixel density, and the panel degrades under continuous ultraviolet exposure. Evidence specific to LCD-printed provisionals remains thinner than for SLA and DLP, although wear studies including LCD-printed specimens have found performance comparable to other digital methods (Çiçek & Küçük, 2025).

2.2.4 Fused Deposition Modeling (FDM)

FDM operates on an entirely different principle: a thermoplastic filament is heated above its softening point and extruded through a moving nozzle, depositing successive beads that fuse as they cool. Its performance in provisional prosthodontics is poor. In comparative flexural testing, FDM specimens neither fractured nor sustained load in a clinically meaningful way but simply deformed under indentation (Park et al., 2020). Layer adhesion in extrusion-based printing is weaker than the covalent network formed in photopolymerized resins, and the resulting anisotropy makes mechanical behaviour direction-dependent. FDM therefore has

little place in the production of definitive-quality provisionals; its role is confined to study models, surgical templates, and other auxiliary devices.

2.3 Comparison of Printing Technologies

Table 2. Characteristics of additive manufacturing technologies used for provisional restorations.

Technology	Light source	Layer exposure	Resolution determinant	Speed	Suitability
SLA	UV laser	Point-by-point trace	Laser spot diameter	Slow	High
DLP	Projector + DMD	Whole layer	Pixel size / build area	Fast	High
LCD	UV LED + LCD mask	Whole layer	Panel pixel density	Fast	Moderate-high
FDM	Heated nozzle	Bead deposition	Nozzle diameter	Moderate	Not recommended

Compiled from Liang et al. (2025), Park et al. (2020), and Yıldırım et al. (2025).

3. The Digital Workflow

Whichever fabrication route is chosen, the preceding steps are shared. An intraoral scanner captures the preparation, adjacent teeth, and opposing arch; the dataset is imported into CAD software where margins are marked, the insertion axis is defined, and the restoration is designed against the planned emergence profile and occlusal scheme. Cement space is specified digitally at this stage, a parameter with direct consequences for seating and marginal discrepancy that has no real equivalent in conventional technique (Alharbi et al., 2018).

Post-processing differs markedly between the two routes and is frequently underestimated. Milled restorations require only separation from the block and modest polishing (Rexhepi et al., 2023). Printed restorations must be washed in solvent to remove uncured resin, separated from their supports, post-cured under controlled light and temperature, and finished where support marks remain; each of these steps introduces variability and influences the final properties of the restoration (Pacheco et al., 2025).

The design stage itself is beginning to change. Deep learning tools can now extract preparation margins automatically from three-dimensional surface data (Alsheghri et al., 2025), and generative models propose complete crown morphology from scans of the preparation and antagonist (Ding et al., 2023; Yang et al., 2025). This evidence concerns definitive crowns; AI-assisted design has not yet been evaluated specifically for provisional restorations. Because provisionals are frequently designed under time pressure, automated margin detection may eventually reduce operator-dependent variability in marginal fit, but for now the clinician's role is to validate rather than delegate the design (Kois et al., 2025).

4. Mechanical Properties

4.1 Flexural Strength and Fracture Toughness

Flexural strength is the property most consistently reported in the comparative literature, yet the evidence does not point in a single direction. A systematic review and meta-analysis found 3D-printed provisional resins superior to both conventional and milled materials in compressive strength, flexural strength, elastic modulus, and wear resistance, but inferior in fracture toughness, resilience, and microhardness; colour stability, water sorption, and solubility were also inferior, and surface roughness results were contradictory (Jain et al., 2022). Other comparative work has favoured milled provisionals on mechanical grounds (Valenti et al., 2024; Yılmaz & Yeşil, 2025).

Individual studies illustrate the split. In a direct comparison of two printed and two conventional interim resins, the printed materials reached markedly higher flexural values than the auto-polymerized and heat-cured acrylic controls (Pantea et al., 2022). Conversely, comparisons of additive, subtractive, and conventional techniques have placed milled materials at or near the top of the ranking (Yılmaz & Yeşil, 2025), and in three-unit prostheses milled frameworks have outperformed printed ones (Abad-Coronel et al., 2021). Across the systematic reviews, all studies reporting flexural strength exceeded the 50 MPa minimum specified for fixed provisional prostheses by ANSI/ADA Specification No. 27 (Alzahrani et al., 2023).

Two explanations reconcile these findings. The first is material heterogeneity printed resins are a rapidly expanding family of formulations, and the same hardware produces very different outcomes depending on resin chemistry, build orientation, layer thickness, and post-curing protocol (Saini et al., 2024; Gad & Fouda, 2023; Çakmak et al., 2024). Build orientation in particular has been the subject of dedicated systematic reviews in provisional restorations (Alqarawi, 2025; Alghauli et al., 2025). Milled PMMA, by contrast, arrives at the clinic in a state already fixed by industrial polymerization, and its properties are correspondingly reproducible.

The second explanation is that flexural strength alone is an incomplete predictor of clinical performance. A material may resist bending to a higher load yet propagate a crack more readily once one forms. The meta-analytic pattern printed resins stronger in flexure but weaker in fracture toughness and resilience (Jain et al., 2022) is therefore clinically meaningful rather than contradictory. In provisional restorations, failures typically initiate at

connectors, margins, or internal defects, where resistance to crack propagation matters more than peak bending strength. The practical distinction is not that one route is simply stronger, but that milled PMMA offers more predictable and tougher behaviour, while printed resins may offer higher flexural values with greater variability and lower damage tolerance.

Efforts to improve printable resins increasingly target the material itself. Adding 10–20 wt% zirconia nanoparticles or 5 wt% glass silica fillers to a DLP-printed temporary crown resin significantly increased flexural strength while maintaining cell viability above 80% (Alshamrani et al., 2023), and zirconia reinforcement has been evaluated for both mechanical performance and antimicrobial efficiency (Aati et al., 2022). The effect interacts with printing orientation (AlGhamdi et al., 2025), and nanoparticle addition also alters the surface and colour properties of printed provisionals (AlGhamdi et al., 2024). Whether such reinforcement also improves fracture toughness in provisional resins specifically the more clinically relevant question has not yet been established.

4.2 Fracture Resistance

Fracture testing on anatomically shaped restorations translates more directly to clinical expectation than bar specimens. Among milled polymers for three-unit prostheses the ranking places PMMA lowest, followed by acetal resin, graphene-modified PMMA, and polysulfone highest (**Table 1**), with all materials exceeding physiological posterior masticatory loads (Abad-Coronel et al., 2023; Henderson et al., 2022).

Failure mode deserves as much attention as failure load. A restoration that deforms before fracturing gives clinical warning of impending failure, whereas a brittle one fails abruptly; this distinction becomes more important as the intended service period lengthens.

4.3 Behaviour After Ageing

Data generated on freshly fabricated specimens overstate clinical performance. Thermocycling protocols of 5000 cycles, taken to approximate several years of intraoral service, reveal changes that static testing misses (Taşın & Ismatullaev, 2022). Water sorption and solubility, which drive hydrolytic degradation, are among the properties in which printed provisional resins perform worse than conventional and milled materials (Jain et al., 2022). Ageing does not affect all materials equally, and in several studies it narrows the gap between fabrication methods rather than widening it (Taşın & Ismatullaev, 2022). A finding relevant to long-term provisionalization, where the relevant comparison is not between new restorations but between restorations already in function for months.

5. Marginal Accuracy and Internal Fit

Marginal adaptation is where digital fabrication has its clearest clinical justification, and where the evidence is most consistent (Al Wadei et al., 2022).

Milled restorations show smaller and more uniform marginal discrepancies than printed ones in most comparative work. An in vitro study reported mean marginal gaps of $73.1 \pm 7.0 \mu\text{m}$ for milled and $95.8 \pm 8.5 \mu\text{m}$ for printed provisional crowns, a statistically significant difference with a large effect size (AlMutairi, 2025). In a prospective within-subject clinical study in which each of 22 participants received a self-cure PMMA, a CAD/CAM-milled PMMA, and a 3D-printed provisional crown, milled crowns provided the best combination of marginal adaptation and mechanical durability (Sarfaraz et al., 2026).

Contrary findings exist. At least one study observed better vertical marginal gaps in printed crowns than in milled ones (Haggag, 2024), and others have reported comparable fit between the two routes (Mohajeri et al., 2021). The inconsistency appears driven less by the fabrication principle than by build orientation, layer thickness, finish line geometry, and support placement, all of which have been shown individually to affect marginal accuracy in printed restorations (Alharbi et al., 2018; Çakmak et al., 2024; Abdelhady et al., 2026). A systematic review concluded that a $50 \mu\text{m}$ layer thickness combined with an intermediate build orientation is critical to keeping marginal and internal gaps within the clinically accepted threshold of $120 \mu\text{m}$ (Abdelhady et al., 2026).

Two points matter for clinical interpretation. First, both digital methods produce discrepancies within commonly accepted clinical thresholds; the debate concerns degree, not acceptability (Al Wadei et al., 2022; Yılmaz & Yeşil, 2025). Second, the consistency of milled restorations may be of greater practical value than a marginal advantage in mean gap, since it is the outlier restoration rather than the average one that causes gingival inflammation during the provisional phase.

6. Esthetic and Surface Properties

6.1 Colour Stability

Colour stability determines how long a provisional restoration remains esthetically acceptable. Testing CAD-CAM PMMA specimens after 5000 thermocycles followed by immersion in coffee, cola, or red grape juice, printed PMMA discoloured significantly more than milled PMMA at seven days, with the difference diminishing at later intervals (Angwaravong et al., 2025). A further comparison of interim restorations confirmed higher colour stability in

milled PMMA than in printed PMMA and identified coffee as a stronger staining agent than tea (Aly et al., 2026), and meta-analytic data likewise show inferior colour stability for printed provisional resins relative to conventional and milled materials (Jain et al., 2022).

The disadvantage is therefore specific to the comparison with milled material. In the clinical study cited above, printed crowns showed better colour stability than self-cure PMMA (Sarfraz et al., 2026). The mechanism is plausible: photopolymerized printed resins retain more unreacted monomer and possess a less densely cross-linked network than industrially polymerized PMMA, leaving them more permeable to pigment (Berghaus et al., 2023; Taşın et al., 2022).

Surface coating offers a practical remedy. Resin glaze applied to either material reduces discoloration, and the benefit is greatest in printed restorations, with coated specimens maintaining clinically acceptable colour for a period corresponding to roughly six months of intraoral service (Angwaravong et al., 2025).

6.2 Surface Roughness

Surface roughness governs plaque accumulation and therefore the periodontal response to a provisional restoration; the threshold above which bacterial adhesion increases substantially is generally taken as 0.2 μm (Bollen et al., 1997). For printed provisional resins the evidence on roughness is contradictory: meta-analysis found no consistent direction of difference relative to conventional and milled materials (Jain et al., 2022), and individual comparisons of printed, conventional, and milled interim materials vary with resin and finishing protocol (Taşın et al., 2022). Whatever the initial roughness, careful finishing and polishing can bring the surface within acceptable limits; discoloration cannot be corrected the same way.

6.3 Wear Behaviour

Wear resistance affects occlusal stability over the provisional period, since loss of occlusal contact through abrasion can shorten the functional life of the restoration and destabilize the planned occlusal scheme (Myagmar et al., 2021). The evidence here runs counter to the general pattern favouring milling. A chewing-simulation study comparing LCD-printed, DLP-printed, conventional bis-acryl, and milled interim resins found printed and milled resins to have wear resistance comparable to conventional material (Çiçek & Küçük, 2025). Earlier work reported methacrylate-based printed resins to exceed both conventional and milled PMMA in wear resistance, with lower volume loss after 30,000 and 60,000 chewing cycles

(Myagmar et al., 2021), and meta-analytic data point in the same direction (Jain et al., 2022). Long-term clinical wear data for printed provisionals are, however, lacking.

7. Biocompatibility and Residual Monomer

Photopolymerization is inherently incomplete. As the resin network vitrifies during curing, chain mobility becomes restricted and a fraction of the monomer remains unreacted and physically entrapped within the matrix (Berghaus et al., 2023). Once eluted into saliva or crevicular fluid, residual monomers can diffuse into adjacent tissues and trigger oxidative stress and cell death; elevated concentrations have been associated with cytotoxicity, mucosal irritation, and inflammatory responses (Arossi et al., 2024).

The final degree of conversion, and hence the residual-monomer burden, depends strongly on post-processing. A review of 3D-printed acrylic resins concluded that adequate washing and post-curing protocols are decisive in minimizing cytotoxic risk (Arossi et al., 2024), and a systematic review of post-processing reached the same conclusion for prosthodontic applications (Cabrol et al., 2024). In a study of two interim printing resins, both materials were cytocompatible irrespective of the layer exposure time and post-curing duration tested, although residual monomer leaching, surface roughness, trueness, and colour stability were all affected by these parameters (Pacheco et al., 2025).

Milled PMMA has a structural advantage here. Industrial polymerization under heat and pressure yields a high degree of conversion with minimal residual monomer, and no operator-dependent post-processing step stands between the block and the finished restoration (Berghaus et al., 2023). The clinical implication is that a printed provisional is only as biocompatible as its post-processing: abbreviated washing or curing, a real temptation under chairside time pressure, compromises both mechanical and biological performance.

8. Cementation and Bonding

Provisional cement selection depends on the degree of retention available, the anticipated service duration, the fabrication technique, and pulp vitality; the restoration must be retained reliably yet remain removable without damage (Burns et al., 2003).

Surface treatment behaves differently between the two fabrication routes. In a direct comparison, milled PMMA achieved higher shear bond strength after airborne-particle abrasion with aluminium oxide, whereas printed PMMA showed higher bond strength without any surface treatment (Aly et al., 2026). This is a clinically useful distinction: routine

sandblasting of a printed provisional may not deliver the benefit expected from milled restorations.

9. Repair

Long-term provisionals fracture, and chairside repair is often preferable to refabrication. The materials commonly used are autopolymerizing PMMA, bis-acryl, and flowable composite resin.

Repair bond strength depends jointly on the repair material and the surface treatment applied. In aged 3D-printed methacrylate provisional resin, the most effective protocols combined airborne-particle abrasion, airborne-particle abrasion with a universal adhesive, or a universal adhesive alone, followed by flowable composite as the repair material (Taokhampu et al., 2025). Surface treatment significantly influenced bond strength in printed temporary restorations, and repair bond strength was consistently lower than the initial fracture strength across all groups (Dinçer et al., 2025).

A repaired provisional should therefore be regarded as a temporary measure within a temporary measure, not a restoration of full function.

10. Clinical Applications and Material Selection

10.1 Short-Term Provisionalization

For single crowns or short-span bridges worn for a few weeks, all three approaches conventional chairside, milling, and printing produce clinically acceptable results. The determining factors become chairside time, cost, and available equipment rather than material performance. Printing offers particular efficiency here, since several units can be produced simultaneously and the clinician is not occupied during fabrication (Liang et al., 2025).

10.2 Long-Term Provisionalization

When the provisional must function for months — during implant osseointegration, periodontal therapy, orthodontic treatment, or extensive rehabilitation — material requirements change substantially (Burns et al., 2003). The evidence supports milling for these indications: milled PMMA provides more reproducible mechanical behaviour and higher fracture toughness (Jain et al., 2022; Abad-Coronel et al., 2023), the most consistent marginal adaptation (Sarfaraz et al., 2026), superior resistance to discoloration (Angwaravong et al., 2025; Aly et al., 2026), and freedom from post-processing-dependent residual monomer (Berghaus et al., 2023). Subtractive fabrication has been recommended for cases requiring

extended provisional service (Yılmaz & Yeşil, 2025), and milled PMMA is accepted for restorations intended to function up to a year (Rexhepi et al., 2023). Wear behaviour is the one parameter where printed materials may hold an advantage (Çiçek & Küçük, 2025; Myagmar et al., 2021).

10.3 Implant-Supported Provisionals

Implant provisionals carry the additional function of shaping peri-implant soft tissue, which places a premium on precise emergence profile reproduction and on the ability to modify the restoration incrementally without compromising its integrity. Milled PMMA suits this role and can be combined with titanium bases for screw-retained designs (Strasding et al., 2024). For full-arch immediate loading, mechanical demands approach the upper limit of what polymeric provisional materials deliver, and direct comparative clinical data remain limited.

10.4 Cost and Efficiency

Printing consumes material only where the object is formed, avoids bur wear, and permits simultaneous production of multiple units — advantages that scale with case volume (Liang et al., 2025). Equipment cost is also lower, particularly for LCD systems. Against this must be set the post-processing burden: solvent washing, support removal, post-curing, and finishing all consume staff time and introduce failure points (Pacheco et al., 2025). Milling has the opposite profile: higher consumable cost, simpler post-processing. For a practice producing occasional single-unit provisionals, milling's simplicity may outweigh its consumable cost; for a laboratory producing many units, printing's throughput advantage dominates.

10.5 A Practical Framework

Table 3. Clinical variables guiding selection between subtractive and additive fabrication.

Clinical variable	Favours milling	Favours printing
Service duration	Months	Weeks
Functional load	High	Moderate
Span	Long-span, full-arch	Single unit, short span
Esthetic demand	High (anterior)	Moderate (posterior)
Number of units	Few	Many simultaneously
Geometric complexity	Simple	Complex
Available time	Flexible	Chairside efficiency critical
Consumable cost sensitivity	Low	High

Rather than asking which technology is superior, the more useful question is which is appropriate to the case at hand. Conventional chairside fabrication retains its place where digital infrastructure is unavailable or where a single-visit repair is required.

11. Limitations of the Current Evidence

Three limitations qualify everything above. First, the evidence base is overwhelmingly *in vitro*. Standardized specimens loaded to failure in a universal testing machine describe material behaviour, not performance in a mouth subject to parafunction, variable pH, thermal cycling, and patient-dependent hygiene; the few clinical studies available involve short observation periods and small samples (Sarfaraz et al., 2026).

Second, material heterogeneity confounds comparison. Studies grouping products as printed resin aggregate materials with different chemistries and processing parameters, which explains much of the inconsistency in published flexural strength data (Saini et al., 2024; Yıldırım et al., 2025). Meaningful conclusions require the fabrication method, the specific material, and the processing protocol to be reported together, a standard the literature does not yet consistently meet (Danila et al., 2025).

Third, the field moves faster than the evidence. Printed resin formulations introduced since the cited studies were designed may already have closed the gaps those studies documented, and nanomodified and highly filled printable materials are changing the picture further. Conclusions about relative performance carry an implicit expiry date.

12. Conclusions

Digital fabrication has become the standard route for provisional restorations in contemporary fixed prosthodontics, and the shift is justified by measurable improvements in mechanical performance, marginal adaptation, and reproducibility over conventional chairside technique.

Between the two digital routes, current evidence favours milling for demanding indications. Milled PMMA benefits from industrial polymerization that chairside and printing processes cannot replicate, and this advantage manifests as greater fracture toughness, more reproducible mechanical behaviour, more consistent marginal fit, superior colour stability, and negligible residual monomer. Additive manufacturing offers compelling advantages in efficiency, material economy, and geometric freedom; printed resins can match or exceed milled materials in flexural strength and wear resistance and perform acceptably for short-term applications, but their output remains more variable, less damage-tolerant, and more dependent on correct parameter selection and post-processing.

The most defensible position is therefore not a preference for one technology but a case-based selection between them, informed by expected service duration, functional load, esthetic demand, and practice logistics. As printed resin formulations mature including nanoparticle reinforced formulations and printing protocols become standardized, this balance is likely to shift; until long-term clinical data accumulate, however, the conservative choice for extended provisionalization remains subtractive manufacturing.

References

- Aati, S., Shrestha, B., & Fawzy, A. (2022). Cytotoxicity and antimicrobial efficiency of ZrO₂ nanoparticles reinforced 3D printed resins. *Dental Materials*, 38(8), 1432-1442.
- Abad-Coronel, C., Calle, C., Abril, G., Paltán, C. A., & Fajardo, J. I. (2023). Fracture resistance analysis of CAD/CAM interim fixed prosthodontic materials: PMMA, graphene, acetal resin and polysulfone. *Polymers*, 15(7), 1761.
- Abad-Coronel, C., Carrera, E., Mena Córdova, N., Fajardo, J. I., & Aliaga, P. (2021). Comparative analysis of fracture resistance between CAD/CAM materials for interim fixed prosthesis. *Materials*, 14(24), 7791.
- Abdelhady, W., Abozaid, D., Mohammed, M., Ashraf, M., Metwally, M., & Mohammed, H. (2026). A systematic review on influence of printing layer thickness on the marginal and internal fit of 3D-printed fixed dental prostheses. *Odontology*, 114, 1021-1043.
- Al Wadei, M. H. D., Sayed, M. E., Jain, S., Aggarwal, A., Alqarni, H., & Gupta, S. G. (2022). Marginal adaptation and internal fit of 3D-printed provisional crowns and fixed dental prosthesis resins compared to CAD/CAM-milled and conventional provisional resins: A systematic review and meta-analysis. *Coatings*, 12, 1777.
- AlGhamdi, M. A., Alatiyyah, F. M., Almedarham, R. F., Al Dawood, Z. H., Alshaikhnasser, F. Y., & Alboryh, S. Y. (2024). Impact of nanoparticle addition on the surface and color properties of three-dimensional (3D) printed polymer-based provisional restorations. *Nanomaterials*, 14(8), 665.
- AlGhamdi, M. A., Alatiyyah, F. M., Dawood, Z. H. A., Alshaikhnasser, F. Y., Almedarham, R. F., Alboryh, S. Y., Elakel, A., Akhtar, S., Khan, S. Q., & Gad, M. M. (2025). Flexural strength of 3D-printed nanocomposite provisional resins: Impact of SiO₂ and ZrO₂ nanoparticles and printing orientations in vitro. *Journal of Prosthodontics*, 34(5), 500-510.
- Alghauli, M. A., Almutairi, S., Almuzaini, S., Aljohani, R., Aljohani, W., & Alqutaibi, A. Y. (2025). Properties and behavior of additively manufactured provisional fixed dental prostheses: A systematic review on 3D printing orientations relative to applied materials and postprocessing. *Journal of Esthetic and Restorative Dentistry*.
- Alharbi, N., Alharbi, S., Cuijpers, V. M. J. I., Osman, R. B., & Wismeijer, D. (2018). Three-dimensional evaluation of marginal and internal fit of 3D-printed interim restorations

- fabricated on different finish line designs. *Journal of Prosthodontic Research*, 62(2), 218-226.
- AlMutairi, R. M. (2025). In-vitro marginal fit of 3D-printed vs milled provisional crowns. *Journal of Pioneering Medical Sciences*, 14(S2), 176-180.
- Alqarawi, F. K. (2025). The influence of printing orientation on the properties of 3D-printed polymeric provisional dental restorations: A systematic review and meta-analysis. *Journal of Functional Biomaterials*, 16(8), 278.
- Alshamrani, A., Alhotan, A., Kelly, E., & Ellakwa, A. (2023). Mechanical and biocompatibility properties of 3D-printed dental resin reinforced with glass silica and zirconia nanoparticles: In vitro study. *Polymers*, 15(11), 2523.
- Alsheghri, A., Zhang, Y., Keren, J., Cheriet, F., & Guibault, F. (2025). Automatic margin line extraction using 3D deep learning on digital surface models of prepared teeth for crown generation. *Computers in Biology and Medicine*, 196, 110960.
- Aly, Y. M., Fahmy, M. H., & Sweid, N. (2026). Evaluation of color stability and bond strength of interim restorations fabricated by CAD/CAM and 3D printing: An in vitro study. *BMC Oral Health*, 26(1), 700.
- Alzahrani, S. J., Hajjaj, M. S., Azhari, A. A., Ahmed, W. M., Yeslam, H. E., & Carvalho, R. M. (2023). Mechanical properties of three-dimensional printed provisional resin materials for crown and fixed dental prosthesis: A systematic review. *Bioengineering*, 10(6), 663.
- Angwaravong, O., Sirichay, S., Pengsuk, T., Sooksuwan, P., & Angwarawong, T. (2025). Effect of surface coating, thermocycling, and staining solutions on the color stability of CAD-CAM polymethyl methacrylate interim fixed restorations. *Journal of Esthetic and Restorative Dentistry*, 37(10), 2270-2280.
- Arossi, G. A., Abou Abdou, N., et al. (2024). Safety of 3D-printed acrylic resins for prosthodontic appliances: A comprehensive cytotoxicity review. *Applied Sciences*, 14(18), 8322.
- Astudillo-Rubio, D., Delgado-Gaete, A., Bellot-Arcís, C., Montiel-Company, J. M., Pascual-Moscardó, A., & Almerich-Silla, J. M. (2018). Mechanical properties of provisional dental materials: A systematic review and meta-analysis. *PLoS ONE*, 13(2), e0193162.

- Berghaus, E., Klocke, T., Maletz, R., & Petersen, S. (2023). Degree of conversion and residual monomer elution of 3D-printed, milled and self-cured resin-based composite materials for temporary dental crowns and bridges. *Journal of Materials Science: Materials in Medicine*, 34(5), 23.
- Bollen, C. M., Lambrechts, P., & Quirynen, M. (1997). Comparison of surface roughness of oral hard materials to the threshold surface roughness for bacterial plaque retention: A review of the literature. *Dental Materials*, 13(4), 258-269.
- Burns, D. R., Beck, D. A., & Nelson, S. K. (2003). A review of selected dental literature on contemporary provisional fixed prosthodontic treatment: Report of the Committee on Research in Fixed Prosthodontics of the Academy of Fixed Prosthodontics. *The Journal of Prosthetic Dentistry*, 90(5), 474-497.
- Cabrol, A., Chuy, V., Fron-Chabouis, H., & Naveau, A. (2024). Effectiveness of postprocessing on 3D printed resin biocompatibility in prosthodontics: A systematic review. *The Journal of Prosthetic Dentistry*.
- Chavali, R., Nejat, A. H., & Lawson, N. C. (2017). Machinability of CAD-CAM materials. *The Journal of Prosthetic Dentistry*, 118(2), 194-199.
- Danila, A. I., Breban-Schwarzkopf, D., Daescu, E., Olariu, I., & Dinu, S. (2025). Systematic review of the quality of stereolithographic three-dimensionally printed materials for provisional dental restorations. *Materials*, 18(3), 721.
- Ding, H., Cui, Z., Maghami, E., Chen, Y., Matinlinna, J. P., & Pow, E. H. N. (2023). Morphology and mechanical performance of dental crown designed by 3D-DCGAN. *Dental Materials*, 39(3), 320-332.
- Dinçer, N., Külünk, Ş., Kısakürek, S., & Duran, I. (2025). Evaluation of the flexural and repair bond strengths of 3D-printed temporary restorations. *BMC Oral Health*, 25(1), 1487.
- Gad, M. M., & Fouda, S. M. (2023). Factors affecting flexural strength of 3D-printed resins: A systematic review. *Journal of Prosthodontics*, 32(S1), 96-110.
- Haggag, M. M. (2024). Effect of two fabrication techniques (CAD/CAM and 3D printing) on the internal fit, marginal adaptation and fracture resistance of multiple fused provisional restorations: An in vitro study. *Advanced Dental Journal*, 6(4), 853-864.

- Henderson, J. Y., Koriath, T. V. P., Tantbirojn, D., & Versluis, A. (2022). Failure load of milled, 3D-printed, and conventional chairside-dispensed interim 3-unit fixed dental prostheses. *The Journal of Prosthetic Dentistry*, 127(2), 275.e1-275.e7.
- Jain, S., Sayed, M. E., Shetty, M., Alqahtani, S. M., Al Wadei, M. H. D., & Gupta, S. G. (2022). Physical and mechanical properties of 3D-printed provisional crowns and fixed dental prosthesis resins compared to CAD/CAM milled and conventional provisional resins: A systematic review and meta-analysis. *Polymers*, 14(13), 2691.
- Karaokutan, I., Sayin, G., & Kara, O. (2015). In vitro study of fracture strength of provisional crown materials. *The Journal of Advanced Prosthodontics*, 7(1), 27-31.
- Khng, K. Y. K., Ettinger, R. L., Armstrong, S. R., Lindquist, T., Gratton, D. G., & Qian, F. (2016). In vitro evaluation of the marginal integrity of CAD/CAM interim crowns. *The Journal of Prosthetic Dentistry*, 115(5), 617-623.
- Kois, J. C., Zeitler, J. M., Barmak, A. B., et al. (2025). Discrepancies in the occlusal devices designed by an experienced dental laboratory technician and by 2 artificial intelligence-based automatic programs. *The Journal of Prosthetic Dentistry*, 134, 214-221.
- Liang, X., Yu, B., Dai, Y., Wang, Y., Hu, M., Zhong, H.-J., & He, J. (2025). Three-dimensional printing resin-based dental provisional crowns and bridges: Recent progress in properties, applications, and perspectives. *Materials*, 18(10), 2202.
- Mangtani, V., Sonkesriya, S., Gupta, A., Chansoria, H., Tripathi, A., & Gupta, S. (2025). Fracture resistance of direct versus CAD-CAM PMMA provisional restorations: An in vitro study. *Bioinformation*. <https://doi.org/10.6026/973206300213395>
- Mohajeri, M., Khazaei, S., Vafaei, F., Firouz, F., Ghorbani Gholiabad, S., & Shisheian, A. (2021). Marginal fit of temporary restorations fabricated by the conventional chairside method, 3D printing, and milling. *Frontiers in Dentistry*, 18, 31.
- Myagmar, G., Lee, J. H., Ahn, J. S., Yeo, I. L., Yoon, H. I., & Han, J. S. (2021). Wear of 3D printed and CAD/CAM milled interim resin materials after chewing simulation. *The Journal of Advanced Prosthodontics*, 13(3), 144-151.
- Pacheco, L. E., Cassiano, F. B., Stuani, V. T., Silva, I. S. P. da, Alamo, L., Costa, M. C. de, Lovison, M. F., Ishikiriyama, S. K., Mondelli, R. F. L., & Soares, D. G. (2025).

- Properties of 3D-printed resins for interim restorations: Effects of printing and post-curing protocols. *Brazilian Oral Research*, 39, e019.
- Pantea, M., Ciocoiu, R. C., Greabu, M., Totan, A. R., Imre, M., Țâncu, A. M. C., Sfeatcu, R., Spînu, T. C., Ilinca, R., & Petre, A. E. (2022). Compressive and flexural strength of 3D-printed and conventional resins designated for interim fixed dental prostheses: An in vitro comparison. *Materials*, 15(9), 3075.
- Park, S.-M., Park, J.-M., Kim, S.-K., Heo, S.-J., & Koak, J.-Y. (2020). Flexural strength of 3D-printing resin materials for provisional fixed dental prostheses. *Materials*, 13(18), 3970.
- Rayyan, M. M., Aboushelib, M., Sayed, N. M., Ibrahim, A., & Jimbo, R. (2015). Comparison of interim restorations fabricated by CAD/CAM with those fabricated manually. *The Journal of Prosthetic Dentistry*, 114(3), 414-419.
- Rexhepi, I., Santilli, M., D'Addazio, G., Tafuri, G., Manciocchi, E., Caputi, S., & Sinjari, B. (2023). Clinical applications and mechanical properties of CAD-CAM materials in restorative and prosthetic dentistry: A systematic review. *Journal of Functional Biomaterials*, 14(8), 431.
- Rosenstiel, S. F., Land, M. F., & Walter, R. D. (2022). *Contemporary fixed prosthodontics* (6th ed.). Elsevier.
- Saini, R. S., Gurumurthy, V., Quadri, S. A., Bavabeedu, S. S., Abdelaziz, K. M., Okshah, A., Alshadidi, A. A. F., Yessayan, L., Mosaddad, S. A., & Heboyan, A. (2024). The flexural strength of 3D-printed provisional restorations fabricated with different resins: A systematic review and meta-analysis. *BMC Oral Health*.
<https://doi.org/10.1186/s12903-023-03826-x>
- Sarfaraz, H., Shetty, M., Hussain, S., & Shetty, R. (2026). Evaluation and comparison of marginal adaptation, colour stability and fracture resistance of provisional resin crowns fabricated with conventional, CAD-milled and 3D printed techniques: A prospective within-subject clinical study. *BMC Oral Health*.
<https://doi.org/10.1186/s12903-026-08670-3>
- Strasding, M., Marchand, L., Merino, E., Zarauz, C., & Pitta, J. (2024). Material and abutment selection for CAD/CAM implant-supported fixed dental prostheses in partially

- edentulous patients: A narrative review. *Clinical Oral Implants Research*, 35(8), 984-999.
- Taokhampu, N., Lekatana, H., & Palasuk, J. (2025). Bond strength of aged provisional 3D-printed methacrylate resin with different surface treatments and repair materials. *BMC Oral Health*, 25(1), 789.
- Taşın, S., & Ismatullaev, A. (2022). Comparative evaluation of the effect of thermocycling on the mechanical properties of conventionally polymerized, CAD-CAM milled, and 3D-printed interim materials. *The Journal of Prosthetic Dentistry*, 127(1), 173.e1-173.e8.
- Taşın, S., Ismatullaev, A., & Usumez, A. (2022). Comparison of surface roughness and color stainability of 3-dimensionally printed interim prosthodontic material with conventionally fabricated and CAD-CAM milled materials. *The Journal of Prosthetic Dentistry*, 128(5), 1094-1101.
- Valenti, C., Isabella Federici, M., Masciotti, F., Marinucci, L., Xhimitiku, I., & Cianetti, S. (2024). Mechanical properties of 3D-printed prosthetic materials compared with milled and conventional processing: A systematic review and meta-analysis of in vitro studies. *The Journal of Prosthetic Dentistry*, 132(2), 381-391.
- Yang, S., Han, J. Y., Lim, S. H., Kim, S., Lee, J., Kim, K. S., Kim, J. M., & Yi, W. J. (2025). DCrownFormer+: Morphology-aware mesh generation and refinement transformer for dental crown prosthesis from 3D scan data of preparation and antagonist teeth. *Medical Image Analysis*, 105, 103717.
- Yıldırım, Ö., Yeşil, Z., & Hatipoğlu, Ö. (2025). Effect of different 3D-printing systems on the flexural strength of provisional fixed dental prostheses: A systematic review and network meta-analysis of in vitro studies. *BMC Oral Health*, 25, 82.
- Yılmaz, G., & Yeşil, Z. (2025). A new era in provisional restorations: Evaluating marginal accuracy and fracture strength in additive, subtractive and conventional techniques. *BMC Oral Health*, 25, 909.
- Çakmak, G., Cuellar, A. R., Donmez, M. B., Schimmel, M., Abou-Ayash, S., Lu, W. E., & Yılmaz, B. (2024). Effect of printing layer thickness on the trueness of 3-unit interim fixed partial dentures. *The Journal of Prosthetic Dentistry*, 131(4), 718-725.
- Çiçek, Y., & Küçük, C. (2025). Wear of interim resin materials manufactured by 3D printing and CAD/CAM milling following chewing simulation. *BMC Oral Health*, 25(1), 1679.

CHAPTER 5

POTENTIAL RISKS AND CHALLENGES OF ARTIFICIAL INTELLIGENCE IN DENTISTRY: SPECIAL EMPHASIS ON DENTOMAXILLOFACIAL RADIOLOGY

Merve YÜCE¹, Birdal AYKUT², Birsay GÜMRÜ³

¹ Research Assistant, DDS, Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Marmara University, merve.yuce@marmara.edu.tr, ORCID ID: 0009-0001-4011-6388

² Research Assistant, DDS, Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Marmara University, birdal.aykut@marmara.edu.tr, ORCID ID: 0009-0004-7847-9127

³ Professor, DDS, PhD, Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Marmara University, bgumru@marmara.edu.tr, ORCID ID: 0000-0002-7734-4755

Artificial intelligence (AI) broadly refers to technologies capable of performing tasks that normally require human cognitive abilities, including learning, reasoning, and problem-solving. Machine learning, one of the major subsets of AI, uses algorithms to identify patterns in data and make predictions, whereas deep learning, a type of machine learning, uses multilayered artificial neural networks to process larger and more complex datasets (Feng et al., 2025).

The use of AI in dentistry has expanded rapidly, particularly in diagnosis, image analysis, clinical decision-making, treatment planning, and prognosis (Khanagar et al., 2021; Gao et al., 2025). At the same time, the increasing integration of AI into clinical practice has raised important concerns regarding data quality, algorithmic bias, transparency, privacy, reliability, accountability, and professional responsibility (Pethani, 2021; Rokhshad et al., 2023; Feng et al., 2025).

Dentomaxillofacial radiology is a field particularly suited to the application of AI, with systems being developed for image classification, detection, segmentation, and radiographic diagnostic support (Heo et al., 2021). However, the performance of these systems is highly dependent on the quality of imaging data and may be affected by artefacts and other image-related limitations (Heo et al., 2021; Feng et al., 2025). Therefore, although this chapter discusses the general risks and challenges of AI in dentistry, particular emphasis is placed on issues relevant to dentomaxillofacial radiology.

Potential Risks and Challenges Associated with Artificial Intelligence in Dentistry

1. Data quality, representativeness, and generalisability

AI performance is highly dependent on key factors such as the quality, quantity and representativeness of the data used to develop the model. Large and diverse datasets are important to improve the robustness and generalisability beyond the conditions represented in the training data (Feng et al., 2025).

If certain patient groups, disease presentations, or relevant clinical characteristics are underrepresented in the training data, AI models may perform less reliably in these populations and may reproduce or exacerbate existing inequalities. Therefore, the representativeness of the datasets is critical for both the performance of the model and the fairness of clinical decision-making assisted by AI (Feng et al., 2025).

Another potential source of error is data annotation. The clinical and imaging data annotation is generally performed by human experts and is susceptible to intra- and inter-

observer variability. Errors in the annotation phase can be propagated through the learning process and result in unreliable model outputs. Therefore, in addition to the size of the dataset, the quality of data annotation and the reference standard used for model development should be carefully evaluated (Feng et al., 2025).

Many dental AI studies involve data from a small number of institutions, limiting the generalisability of their findings to other clinical settings or patient populations. Hence, the use of diverse multicentre datasets and proper external validation are essential before an AI system can be implemented in broader clinical practice (Krois et al., 2021; Ardila et al., 2026).

2. Reliability and clinical safety

Reliability is an important criterion for the clinical use of AI. AI systems designed for clinical use should be of reliable and clinically acceptable performance and users should be aware of their limitations.

The clinical consequences of AI-related diagnostic errors should also be considered. False-positive findings may lead to unnecessary investigations or interventions, whereas false-negative findings may delay the diagnosis and treatment of clinically significant disease. For this reason, the evaluation of AI systems should consider not only measures of diagnostic performance but also the potential clinical consequences of different types of error. Clinical validation is particularly important before AI systems are introduced into routine healthcare practice (Feng et al., 2025).

3. Ethical and legal challenges

The use of new technologies in healthcare raises ethical considerations for patients, clinicians, developers, and other stakeholders. These concerns are particularly significant when dealing with AI, because AI systems may process sensitive and confidential health information and may influence diagnosis, clinical decision-making, and treatment planning (Rokhshad et al., 2023; Feng et al., 2025).

The main ethical principles relevant to the use of AI in dentistry are autonomy, non-maleficence, beneficence, justice, and veracity (Rokhshad et al., 2023). Autonomy requires that patients be well-informed about their treatment and, where relevant, about the role of AI systems in the decision-making process (Feng et al., 2025). Non-maleficence and beneficence require the use of AI in a manner that minimizes the risk of harm from diagnostic errors or inaccurate recommendations and promotes patient well-being. Justice demands that AI be used

fairly and equally, without reinforcing current inequalities and algorithmic bias. Veracity requires being transparent and honest in explaining how AI-assisted decisions are made (Rokhshad et al., 2023).

Accountability is another important ethical and legal issue. If an AI-assisted decision results in misdiagnosis or patient harm, responsibility may lie with the clinician, healthcare facility, AI developer, or regulatory agency. The problem becomes even more complex if the decision-making process of the AI system is not transparent or explainable (Feng et al., 2025). Clear accountability frameworks are therefore needed to define responsibilities among the stakeholders involved in the development, deployment, and clinical use of AI technologies (Mennella et al., 2024).

4. Data privacy and transparency

As AI systems are increasingly reliant on personal and sensitive health data, concerns of data privacy and confidentiality are becoming increasingly important. Patients should be informed about the usage of their data and the integration of AI-driven systems in clinical decision-making (Duggal and Tripathi, 2024).

Another problem is the risk of re-identification. Under certain conditions, anonymised or pseudonymised data may be re-identified by means of advanced computational techniques. This risk may be particularly relevant to datasets with limited size or containing data on rare diseases or uncommon clinical conditions (Feng et al., 2025).

Transparency is also essential for the responsible use of AI in dentistry. Information regarding data selection, labelling procedures, model development, testing, and validation should be adequately documented (Mongan et al., 2020). Lack of transparency may make it difficult to identify potential biases or limitations and may reduce trust in AI systems. This concern is particularly relevant when AI-generated decisions are difficult to explain or interpret (Feng et al., 2025).

5. Bias, inequality, cost, and access

Bias may arise at any stage of the development and implementation of AI. Biased data, biased sampling, and biased model training may lead to unequal treatment, misdiagnosis, or underdiagnosis in certain patient groups, particularly when the population in which the system is used is not adequately represented in the training data (Rahim et al., 2024).

These issues are closely associated with inequality in access to AI-supported healthcare. Although AI has the potential to expand access to care, particularly in underserved populations, unequal availability of technology and limitations in existing infrastructure may limit these benefits and contribute to disparities between populations and healthcare settings (Bamashmous, 2025; Narad et al., 2026).

Cost represents an additional barrier to widespread implementation. The acquisition of AI systems, hardware, software licences, computing infrastructure, and data-storage capacity may impose substantial financial burdens on dental practices and healthcare institutions, particularly in low-resource settings (Rahim et al., 2024).

6. Patient-dentist relationship, training, and professional autonomy

The patient-dentist relationship is based not only on clinical competence but also on communication, empathy, trust, and shared decision-making. Increased reliance on AI-mediated processes may reduce direct interaction between patients and clinicians and may compromise the therapeutic relationship if technology begins to replace rather than support human interaction. AI should therefore be integrated in a way that supports, rather than replaces, the patient-dentist relationship (Sciarra et al., 2025).

The increasing use of AI may also have implications for professional autonomy. When clinicians become dependent on the AI-generated recommendations, they may become less likely to question or independently evaluate these outputs. This issue is especially pronounced in cases where there is a disagreement between AI-generated and clinician-generated opinions. Therefore, human supervision is still necessary to ensure that final clinical decisions are consistent with professional judgement and patient's individual needs (Feng et al., 2025; Sciarra et al., 2025).

Proper education and training is needed to ensure the safe and responsible use of AI in dental practice. In addition, dental professionals should be able to understand the capabilities and limitations of AI tools and critically evaluate AI-generated results rather than blindly accepting them. AI should be considered as a decision-support tool that complements professional judgement (Kaur et al., 2025).

Special Considerations in Dentomaxillofacial Radiology

Dentomaxillofacial radiology is one of the dental specialties in which AI has been extensively studied, particularly due to the compatibility of radiographic images with computer-

based image analysis. AI applications in this field have been developed for a variety of tasks including image classification, detection, segmentation, radiographic diagnosis, and enhancement of image quality using panoramic and periapical radiographs, cephalometric images, and cone-beam computed tomography. Reported applications are automated localisation of cephalometric landmarks, detection of osteoporosis, classification or segmentation of maxillofacial cysts and tumours, and identification of periodontal or periapical disease (Heo et al., 2021).

Despite these promising applications, the development and clinical use of AI in dentomaxillofacial radiology remain limited by challenges related to data quality, annotation, explainability, and clinical validation (Heo et al., 2021; Feng et al., 2025). Artefacts or poor-quality image data may also be misinterpreted by AI systems and contribute to incorrect diagnostic outputs (Feng et al., 2025). The following sections therefore focus on the main technical and clinical challenges associated with AI in dentomaxillofacial radiology.

1. Image quality, artefacts, and dataset-related challenges

The success of AI systems in dentomaxillofacial radiology is highly correlated with the quality and composition of the imaging data used for model development. High-quality, accurately labelled datasets are essential to train reliable models. However, obtaining sufficiently large and well-organised datasets of dental imaging can be difficult, time-consuming, and expensive (Heo et al., 2021; Uribe et al., 2024).

Availability and quality of dental imaging datasets remain important limitations. Publicly available dental image datasets may be affected by inconsistencies in annotation methods, metadata reporting, and licensing information. Moreover, lack of diversity may limit the robustness and generalisability of AI models. Therefore, increased standardisation and diversity of datasets are important to enhance the reliability of clinical translation (Uribe et al., 2024; Zhang et al., 2026).

Image quality and artefacts may also influence the AI-based interpretation. Radiographic images may contain noise, artefacts, overlapping structures, or other image features that make interpretation difficult by both human and automated systems. The presence of overlapping structures may result in inaccurate labelling. Corrupted or low-quality radiological data may be misinterpreted by AI systems leading to incorrect diagnostic outcomes (Heo et al., 2021; Feng et al., 2025).

2. Annotation and reference standard limitations

In dentomaxillofacial radiology, the quality of image annotation and the reliability of the reference standard used as ground truth are critical in the development and evaluation of AI systems. In dental imaging, ground-truth labels can be generated either by direct image annotation by radiologists or extracted from radiology reports. Inaccurate or poorly defined labels may introduce uncertainty into model training and evaluation (Heo et al., 2021).

Manual annotation is time-consuming and may be affected by intra- and inter-observer variability. This may be especially relevant for two-dimensional dental radiographs, where anatomical structures overlap and accurate delineation may be difficult. If multiple radiologists are involved in the labelling of large datasets, there can also be variations in annotation standards. Therefore, the development of a reliable ground truth requires the assessment of observer agreement and consensus procedures (Heo et al., 2021).

Furthermore, the reference standard for AI development may vary across different diagnostic tasks, which may include expert or consensus annotation, manual segmentation, clinical documentation, or confirmation with additional imaging. The absence of standardisation among these reference standards can influence model training, efficacy reported, and comparisons between datasets as a consequence of differences in the definitions of ground truth or target labels. Well-defined and standardised annotation protocols are critical to increase the reproducibility and clinical interpretability of AI models (Ardila et al., 2026).

3. Generalisability and external validation

Generalisability is a major challenge for the clinical translation of AI systems developed for dental imaging. Good performance by a model on internal test data does not guarantee that it will be equally successful when applied to images originating from different institutions, patient populations, or clinical settings. External validation is therefore important for evaluating whether an AI model has the ability to maintain reliable performance outside its training dataset (Ardila et al., 2026).

This has been directly studied in the field of dental radiology. In a study evaluating the performance of deep learning models in the apical lesion detection, using panoramic radiographs from two centres from Germany and India, it was demonstrated that a model trained on images from one centre performed less effectively on images from the other. Cross-centre training was reported to improve performance on external datasets and the need for training

data reflecting the variability encountered in clinical settings was emphasised (Krois et al., 2021).

Variability in imaging conditions, patient populations, dataset composition, and labelling processes may result in domain shift and reduced generalisability. Since the performance of AI systems may differ in complex cases or under different imaging conditions, they must be tested on independent and diverse datasets before being introduced for widespread clinical use (Math et al., 2025; Ardila et al., 2026).

4. Diagnostic errors and clinical consequences

Diagnostic errors remain a significant concern in AI systems used to assist in interpretation in dentomaxillofacial radiology. AI-supported interpretation can enhance diagnostic accuracy for certain radiological tasks however the performance of the system may vary depending on the complexity of the case and the imaging conditions. A recent systematic review on augmented intelligence in dentomaxillofacial radiology reported increased accuracy in different applications - such as the detection of dental caries and apical pathologies, the segmentation of jaw lesions, and the identification of cephalometric landmarks - while also emphasising that performance may be inconsistent in complex cases or under different imaging conditions (Math et al., 2025).

In studies performed using panoramic radiographs, differences between AI results and clinical interpretations have been reported. Orhan et al. (2023) observed that AI may produce false-positive and false-negative results in different dental conditions and AI-generated findings may not always align with the assessments of human experts. As a result, such findings should not be accepted in isolation but rather evaluated with the clinical and radiographic context.

In the evaluation of the performance of AI, the clinical importance of diagnostic errors should also be considered. False-positive and false-negative results may have distinct consequences in real-world settings; therefore, only diagnostic performance metrics may not fully reflect the potential effect of these outcomes on patient care (Feng et al., 2025). Consequently, a careful clinical validation process is essential before AI systems in the field of dentomaxillofacial radiology can be integrated into routine diagnostic practice (Rahmanzadeh et al., 2025).

5. Black-box decision making and explainability

A major limitation of many AI systems used in diagnostic imaging is the difficulty in understanding how a specific output or decision is obtained. This is described as the “black-box” phenomenon, where the internal processes reaching to an AI-generated result are not easily accessible or interpretable by the user (Feng et al., 2025).

Limited explainability may make it difficult for clinicians to understand why an AI system focuses on a specific region or arrives at a particular classification. This may hinder the detection of errors or biases and reduce the trust of clinicians in AI-supported findings. Therefore, explainability is of great importance for enhancing transparency and supporting the clinical-level acceptance of AI systems in medical imaging (Muhammad and Bendeche, 2024; Feng et al., 2025; Saw et al., 2025).

Explainable AI, which contributes to predictions by providing information about specific image features or regions, aims to make results generated by AI more understandable. In the case of medical imaging, this is often done with visual techniques such as heat maps. However, explanations provided may be difficult for clinicians to interpret; furthermore, an explainable output does not necessarily mean that the model is clinically accurate or reliable (Saw et al., 2025).

6. Automation bias and overreliance

Automation bias and overreliance are potential risks when AI is applied to image analysis. One potential drawback is that radiologists may become over-reliant on the AI results, which could influence the efficacy of human-AI collaboration (Li and Little, 2023). Therefore, maintaining a balanced level of trust in AI systems is essential when using these systems to support radiological interpretation.

The issue of overreliance becomes particularly important when the results generated by AI contradict clinician’s own interpretation. In such cases, the tendency to give more importance to decisions driven by AI than to expert judgment raises questions about which perspective should be prioritised (Feng et al., 2025).

Automation bias can also have professional and medicolegal consequences. Overreliance on AI systems and a tendency to depend on incorrect findings generated by AI may increase the risks of malpractice and liability. Therefore, radiologists should maintain their independent

clinical judgement and view AI as a supportive component - rather than an authoritative one – in the interpretation of images (Mezrich, 2026).

7. Incidental findings in AI-assisted image interpretation

In panoramic radiographs, incidental findings are frequently encountered due to the wide field of view that extends beyond the specific area intended for examination. Such findings may involve the teeth, maxillary sinuses, soft-tissue calcifications, temporomandibular joints, and other craniofacial structures. Although many incidental findings are of limited clinical significance, some may require further diagnostic evaluation or clinical management (Imboden-Ilia et al., 2026).

AI has been investigated for its ability to detect various findings on panoramic radiographs - such as dental caries, periapical lesions, periodontal bone loss, osteoporosis, maxillary sinusitis - as well as identification and numbering of teeth. However, the existing evidence is heterogeneous in nature, therefore caution should be exercised when interpreting the reported diagnostic performance values (Turosz et al., 2023).

The limitations in detecting incidental findings have also been demonstrated through direct comparisons with human experts. In a recent diagnostic accuracy study using CBCT as a reference, multimodal large language models exhibited lower sensitivity, specificity, and overall accuracy compared to dentomaxillofacial radiologists in identifying nine predefined incidental findings on panoramic radiographs. This inconsistency became even more pronounced in cases involving high-risk findings. Consequently, the authors concluded that, under the conditions tested, these models should not be used independently for the interpretation of panoramic images (Çapar et al., 2026). These findings emphasise the need for expert review in the use of AI-assisted systems for the interpretation of panoramic images.

8. Privacy and security of radiographic data

The use of AI systems in dentomaxillofacial radiology necessitates access to large volumes of patient imaging data, including panoramic and periapical radiographs as well as cone-beam computed tomography scans. Such data may contain sensitive information that could identify an individual, raising concerns about privacy, consent, data sharing, and governance (Brinz et al., 2025). Furthermore, dental images may encompass anatomical and restorative features unique to an individual. This increases the potential for re-identification and may create barriers to unrestricted sharing of data between institutions (Ardila et al., 2026).

A further important issue is the ethical management of imaging datasets. A recent systematic review of 105 publicly accessible dentomaxillofacial imaging datasets highlighted that 83.8% lacked information regarding whether ethical approval had been obtained, while only 61.9% specified terms or licences for dataset reuse. The authors stress the need for standardised guidelines on the reuse of datasets and consent processes that ensure patients are adequately informed that their imaging data may be used in AI research (Hao et al., 2025).

Privacy-preserving strategies make it possible to use imaging data from various institutions without sharing raw patient images directly. For example, federated learning allows collaborating institutions to contribute to the development of a common model while keeping patient data in their own systems. However, there is limited data available on the use of this approach in dental imaging, and its application is hampered by technical difficulties, privacy issues, and regulatory challenges (Brinz et al., 2025; Ardila et al., 2026).

9. Education, training, and potential deskilling

With the growing integration of AI into radiological practice, clinicians need to gain competencies beyond the traditional image interpretation skills. Radiology education should include basic knowledge of AI principles, model limitations, bias, and ethical considerations, and the ability to critically evaluate AI-generated outputs instead of accepting them blindly (Jassar et al., 2025; Keshavarz et al., 2026).

Structured AI training can improve participants' knowledge levels, self-confidence, and diagnostic skills. A systematic review of AI training in radiology revealed that the majority of the studies reviewed showed improvements in one or more educational outcome measures. It also reaffirmed the need for standardised curricula, exposure to a wide range of clinical cases, mentorship, and integration of AI training into routine radiology education (Keshavarz et al., 2026).

At the same time, the growing reliance on AI has raised concerns about the potential for deskilling and a reduction in independent diagnostic reasoning. Although there is limited evidence of substantial clinical deskilling, recent findings suggest that automation bias and reduced opportunities to maintain skills may affect professional expertise (Heudel et al., 2026). Therefore, training in AI should promote critical appraisal of automated outputs and retention of independent diagnostic skills, with AI as an adjunct, not a substitute, for traditional radiology education (Hui et al., 2025; Jassar et al., 2025).

10. Clinical validation and safe integration

Diagnostic performance in experimental settings does not necessarily mean that an AI system is ready for routine clinical use. When dealing with dental imaging, validation should include not only internal testing but also using independent datasets, data from different centres, a range of devices, and diverse clinical settings. Current evidence suggests that the translation to clinical practice has been inconsistent; for many AI applications in dentistry, evidence regarding external validation and performance under real-world conditions remains limited (Ardila et al., 2026; Hegde and Vasa, 2026).

Clinical integration should also consider human-AI interaction and workflow rather than model performance alone. Early clinical evaluation should assess how AI systems perform in real clinical settings, including their effects on safety, human factors, and clinical decision-making. Reporting frameworks such as DECIDE-AI emphasise these aspects in the evaluation of AI-based clinical decision-support systems (Vasey et al., 2022).

Safe clinical integration therefore requires more than high diagnostic accuracy. Reproducibility, external validation, workflow compatibility, and human factors should also be considered when determining whether an AI system is ready for broader clinical use. AI should remain a decision-support tool within a clinically accountable human-AI workflow rather than function as a substitute for professional judgement (Vasey et al., 2022; Ardila et al., 2026).

Artificial Intelligence in Other Dental Specialties

Although this chapter primarily focuses on dentomaxillofacial radiology, AI has also been increasingly investigated in other dental specialties.

AI has been used in periodontology for diagnosis of periodontal disease, radiographic assessment of bone loss, disease classification, treatment planning and prediction of treatment outcomes. However, the reliability of these applications depends critically on data quality, while issues related to patient privacy, data protection, and algorithmic bias remain relevant for their clinical use (Akram, 2025).

In the practice of restorative dentistry, the use of AI has been widely investigated for detection and diagnosis of dental caries based on data acquired from radiographs and intraoral photographs. Many studies have shown promising diagnostic performance, but substantial heterogeneity in imaging modalities, diagnostic thresholds, analytical tasks, and evaluation methods limits the reliability and clinical generalisability of the existing evidence. In addition,

there are few external validation studies, and the current evidence does not provide sufficient support to use AI as a standalone diagnostic tool for caries detection (Bittar et al., 2026).

In the field of endodontics, AI has been investigated for applications such as the assessment of root canal anatomy, detection of periapical lesions and root fractures, determination of working length, and prediction of outcomes for retreatment procedures. While these applications have demonstrated a promising level of accuracy and potential for supporting diagnostic and treatment processes, further evidence is required before they can be more broadly integrated into routine endodontic practice (Aminoshariae et al., 2021).

In paediatric dentistry, AI has been explored in terms of diagnostic support, treatment planning, predictive applications, and personalised patient management. However, its use raises specific concerns regarding data privacy, informed consent, algorithmic bias, transparency, and appropriate human oversight. These issues are especially important in paediatric populations because children represent a vulnerable group with limited capacity for consent and require additional safeguards for the use of their personal and health data (Assiry et al., 2025).

In orthodontics, AI has been investigated as a tool to support treatment planning, particularly decisions regarding the need for tooth extraction. A recent systematic review and meta-analysis reported promising diagnostic performance of AI models for predicting orthodontic extraction decisions. However, substantial heterogeneity among the included studies indicates that further large-scale research is needed before these models can be widely implemented in clinical practice (Ziaei et al., 2025).

In prosthodontics and implant dentistry, AI has been investigated for diagnostic and treatment-planning applications, including radiographic implant identification, CBCT-based planning, image segmentation, and prosthesis design. Although promising performance has been reported for several well-defined tasks, evidence for prognostic and more complex decision-making applications remains limited and heterogeneous. Moreover, most of the available evidence is derived from systematic reviews of low or critically low methodological quality. Therefore, AI should be viewed as a supportive tool rather than a replacement for routine clinical practice and professional judgement (Alfaraj et al., 2026).

Conclusion

AI holds significant potential for supporting diagnosis, treatment planning, and clinical decision-making processes in dentistry. However, technical performance alone does not guarantee safe and effective clinical use. When integrating AI systems into clinical practice, factors such as data quality, bias, generalisability, transparency, privacy, accountability, and human-AI interaction remain critically important.

These issues are particularly relevant in dentomaxillofacial radiology, where the performance of AI is closely linked to the quality of imaging data, annotations, reference standards, and external validation. Consequently, findings generated by AI should be interpreted within a broader radiographic and clinical context rather than being used as standalone diagnostic results. Safe clinical integration requires appropriate validation, protection of patient data, professional training, and meaningful human oversight, with AI serving as a supportive tool rather than a replacement for professional judgement.

REFERENCES

- Akram, H. M. (2025). Artificial intelligence in dentistry: Advancements in periodontology and other specialties, diagnosis, treatment planning, and ethical considerations. *Dentistry Review*, 5(2), 100157. <https://doi.org/10.1016/j.dentre.2025.100157>
- Alfaraj, A., Limones, Á., Ahmad, S., Aljubairah, F., Albalaw, S., Albeshar, M., Alghamdei, B., & Lin, W. S. (2026). Harnessing AI in prosthodontics and implant dentistry: An umbrella review of systematic evidence. *Journal of Prosthodontics*, 35(2), 127-142. <https://doi.org/10.1111/jopr.70091>
- Aminoshariae, A., Kulild, J., & Nagendrababu, V. (2021). Artificial intelligence in endodontics: Current applications and future directions. *Journal of Endodontics*, 47(9), 1352-1357. <https://doi.org/10.1016/j.joen.2021.06.003>
- Ardila, C. M., Vivares-Builes, A. M., & Pineda-Vélez, E. (2026). From algorithmic performance to clinical translation: Translational readiness of imaging-based artificial intelligence in dentistry - A systematic review. *Healthcare*, 14(13), 1952. <https://doi.org/10.3390/healthcare14131952>
- Assiry, A. A., Alrehaili, R. S., Mahnashi, A., Alkam, H., Mahdi, R., Hakami, R., Alshammakhy, R., Almallahi, W., Alhawsah, Y., & Khalil, A. S. (2025). How is artificial intelligence transforming the intersection of pediatric and special care dentistry? A scoping review of current applications and ethical considerations. *Prosthesis*, 7(5), 119. <https://doi.org/10.3390/prosthesis7050119>
- Bamashmous, M. (2025). The role of artificial intelligence in transforming dental public health: Current applications, ethical considerations, and future directions. *The Open Dentistry Journal*, 19, e18742106363413. <https://doi.org/10.2174/0118742106363413250211053942>
- Bittar, A., Dascanio, R., & Özcan, M. (2026). Artificial intelligence for dental caries detection: An umbrella review. *Journal of Dentistry*, 175, 106944. <https://doi.org/10.1016/j.jdent.2026.106944>
- Brinz, J., Eslamiamirabadi, N., Salamati, A., Tresp, V., Schwendicke, F., & Tichy, A. (2025). Data sharing for responsible artificial intelligence in dentistry: A narrative review of legal frameworks and privacy-preserving techniques. *Journal of Dentistry*, 163, 106130. <https://doi.org/10.1016/j.jdent.2025.106130>

- Çapar, İ., Hasırcı, U. C., Dumanlı Kusay, D., Altın, E., & Geduk, G. (2026). Comparison of multimodal large language models and oral and maxillofacial radiologists in the detection of incidental findings on panoramic radiographs: A CBCT-referenced diagnostic accuracy study. *Healthcare*, 14(18), 2948. <https://doi.org/10.3390/healthcare14182948>
- Duggal, I., & Tripathi, T. (2024). Ethical principles in dental healthcare: Relevance in the current technological era of artificial intelligence. *Journal of Oral Biology and Craniofacial Research*, 14(3), 317-321. <https://doi.org/10.1016/j.jobcr.2024.04.003>
- Feng, Q. J., Harte, M., Carey, B., Alqarni, A., Monteiro, L., Diniz-Freitas, M., Fricain, J. C., Lodi, G., Brailo, V., Andreoletti, M., & Albuquerque, R. (2025). The risks of artificial intelligence: A narrative review and ethical reflection from an Oral Medicine group. *Oral Diseases*, 31(2), 348-353. <https://doi.org/10.1111/odi.15100>
- Gao, S., Wang, X., Xia, Z., Zhang, H., Yu, J., & Yang, F. (2025). Artificial intelligence in dentistry: A narrative review of diagnostic and therapeutic applications. *Medical Science Monitor*, 31, e946676. <https://doi.org/10.12659/MSM.946676>
- Hao, J., Nalley, A., Yeung, A. W. K., Tanaka, R., Ai, Q. Y. H., Lam, W. Y. H., Shan, Z., Leung, Y. Y., AlHadidi, A., Bornstein, M. M., Tsoi, J. K. H., McGrath, C., & Hung, K. F. (2025). Characteristics, licensing, and ethical considerations of openly accessible oral-maxillofacial imaging datasets: A systematic review. *NPJ Digital Medicine*, 8(1), 412. <https://doi.org/10.1038/s41746-025-01818-5>
- Hegde, S., & Vasa, R. (2026). Assessing the clinical deployability of AI tools for caries detection: A structured narrative synthesis and proposed framework. *Journal of Dentistry*, 172, 106770. <https://doi.org/10.1016/j.jdent.2026.106770>
- Heo, M. S., Kim, J. E., Hwang, J. J., Han, S. S., Kim, J. S., Yi, W. J., & Park, I. W. (2021). Artificial intelligence in oral and maxillofacial radiology: What is currently possible? *Dentomaxillofacial Radiology*, 50(3), 20200375. <https://doi.org/10.1259/dmfr.20200375>
- Heudel, P. E., Crochet, H., Filori, Q., Bachelot, T., & Blay, J. Y. (2026). Artificial intelligence in medicine: A scoping review of the risk of deskilling and loss of expertise among physicians. *ESMO Real World Data and Digital Oncology*, 12, 100693. <https://doi.org/10.1016/j.esmorw.2026.100693>

- Hui, M. L., Sacoransky, E., Chung, A., & Kwan, B. Y. (2025). Exploring the integration of artificial intelligence in radiology education: A scoping review. *Current Problems in Diagnostic Radiology*, 54(3), 332-338. <https://doi.org/10.1067/j.cpradiol.2024.10.012>
- Imboden-Ilia, A., Awaad, H., Inglezos, E., Eliades, T., & Papageorgiou, S. N. (2026). Incidental findings from panoramic radiographs: A systematic review with meta-analysis. *Clinical Oral Investigations*, 30(10), 464. <https://doi.org/10.1007/s00784-026-07148-4>
- Jassar, S., Zhou, Z., Leonard, S., Youssef, A., Probyn, L., Kulasegaram, K., & Adams, S. J. (2025). Educational competencies for artificial intelligence in radiology: A scoping review. *Academic Radiology*, 32(9), 5624-5634. <https://doi.org/10.1016/j.acra.2025.06.044>
- Kaur, N., Jacob, G., Singh, A., Khan, S., Dhir, P., & Kakarla, G. (2025). Artificial intelligence in dentistry: Balancing innovation with ethical responsibility. *Bioinformation*, 21(3), 489-494. <https://doi.org/10.6026/973206300210489>
- Keshavarz, P., Mohammadigoldar, Z., Bedayat, A., Raman, S. S., & Tai, R. (2026). Artificial intelligence education in radiology training: A systematic review of effectiveness, barriers, and future directions. *Academic Radiology*, 33(3), 695-706. <https://doi.org/10.1016/j.acra.2025.10.049>
- Khanagar, S. B., Al-Ehaideb, A., Maganur, P. C., Vishwanathaiah, S., Patil, S., Baeshen, H. A., Sarode, S. C., & Bhandi, S. (2021). Developments, application, and performance of artificial intelligence in dentistry: A systematic review. *Journal of Dental Sciences*, 16(1), 508-522. <https://doi.org/10.1016/j.jds.2020.06.019>
- Krois, J., Garcia Cantu, A., Chaurasia, A., Patil, R., Chaudhari, P. K., Gaudin, R., Gehrung, S., & Schwendicke, F. (2021). Generalizability of deep learning models for dental image analysis. *Scientific Reports*, 11(1), 6102. <https://doi.org/10.1038/s41598-021-85454-5>
- Li, M. D., & Little, B. P. (2023). Appropriate reliance on artificial intelligence in radiology education. *Journal of the American College of Radiology*, 20(11), 1126-1130. <https://doi.org/10.1016/j.jacr.2023.04.019>
- Math, S. Y., Ameli, N., Stefani, C. M., Kung, J. Y., Punithakumar, K., Amin, M., & Pacheco-Pereira, C. (2025). Augmented intelligence in oral and maxillofacial radiology: A

- systematic review. *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, 140(2), 237-250. <https://doi.org/10.1016/j.oooo.2025.03.015>
- Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon*, 10(4), e26297. <https://doi.org/10.1016/j.heliyon.2024.e26297>
- Mezrich, J. L. (2026). Automation bias and overconfidence in artificial intelligence and associated legal implications. *Clinical Imaging*, 132, 110745. <https://doi.org/10.1016/j.clinimag.2026.110745>
- Mongan, J., Moy, L., & Kahn, C. E., Jr. (2020). Checklist for artificial intelligence in medical imaging (CLAIM): A guide for authors and reviewers. *Radiology: Artificial Intelligence*, 2(2), e200029. <https://doi.org/10.1148/ryai.2020200029>
- Muhammad, D., & Bendeche, M. (2024). Unveiling the black box: A systematic review of explainable artificial intelligence in medical image analysis. *Computational and Structural Biotechnology Journal*, 24, 542-560. <https://doi.org/10.1016/j.csbj.2024.08.005>
- Narad, C., Sharda, K., & Aasdhir, S. S. (2026). Ethical dimensions of artificial intelligence integration into dental practice. *Journal of the American Dental Association*, 157(9), 999-1004. <https://doi.org/10.1016/j.adaj.2026.02.004>
- Orhan, K., Aktuna Belgin, C., Manulis, D., Golitsyna, M., Bayrak, S., Aksoy, S., Sanders, A., Önder, M., Ezhov, M., Shamshiev, M., Gusarev, M., & Shlenskii, V. (2023). Determining the reliability of diagnosis and treatment using artificial intelligence software with panoramic radiographs. *Imaging Science in Dentistry*, 53(3), 199-208. <https://doi.org/10.5624/isd.20230109>
- Pethani, F. (2021). Promises and perils of artificial intelligence in dentistry. *Australian Dental Journal*, 66(2), 124-135. <https://doi.org/10.1111/adj.12812>
- Rahim, A., Khatoon, R., Khan, T. A., Syed, K., Khan, I., Khalid, T., & Khalid, B. (2024). Artificial intelligence-powered dentistry: Probing the potential, challenges, and ethicality of artificial intelligence in dentistry. *Digital Health*, 10, 20552076241291345. <https://doi.org/10.1177/20552076241291345>

- Rahmanzadeh, M., Rustamzadeh, A., Gorgich, E. A., Mehrbani, H., & Aghakouchakzadeh, A. (2025). Toward precision diagnosis of maxillofacial pathologies by artificial intelligence algorithms: A systematic review. *Journal of Maxillofacial and Oral Surgery*, 24(4), 1151-1178. <https://doi.org/10.1007/s12663-025-02664-4>
- Rokhshad, R., Ducret, M., Chaurasia, A., Karteva, T., Radenkovic, M., Roganovic, J., Hamdan, M., Mohammad-Rahimi, H., Krois, J., Lahoud, P., & Schwendicke, F. (2023). Ethical considerations on artificial intelligence in dentistry: A framework and checklist. *Journal of Dentistry*, 135, 104593. <https://doi.org/10.1016/j.jdent.2023.104593>
- Saw, S. N., Yan, Y. Y., & Ng, K. H. (2025). Current status and future directions of explainable artificial intelligence in medical imaging. *European Journal of Radiology*, 183, 111884. <https://doi.org/10.1016/j.ejrad.2024.111884>
- Sciarra, F. M., Caivano, G., Cacioppo, A., Messina, P., Cumbo, E. M., Di Vita, E., & Scardina, G. A. (2025). Dentistry in the era of artificial intelligence: Medical behavior and clinical responsibility. *Prosthesis*, 7(4), 95. <https://doi.org/10.3390/prosthesis7040095>
- Turosz, N., Chęcińska, K., Chęciński, M., Brzozowska, A., Nowak, Z., & Sikora, M. (2023). Applications of artificial intelligence in the analysis of dental panoramic radiographs: An overview of systematic reviews. *Dentomaxillofacial Radiology*, 52(7), 20230284. <https://doi.org/10.1259/dmfr.20230284>
- Uribe, S. E., Issa, J., Sohrabniya, F., Denny, A., Kim, N. N., Dayo, A. F., Chaurasia, A., Sofi-Mahmudi, A., Büttner, M., & Schwendicke, F. (2024). Publicly available dental image datasets for artificial intelligence. *Journal of Dental Research*, 103(13), 1365-1374. <https://doi.org/10.1177/00220345241272052>
- Vasey, B., Nagendran, M., Campbell, B., Clifton, D. A., Collins, G. S., Denaxas, S., Denniston, A. K., Faes, L., Geerts, B., Ibrahim, M., Liu, X., Mateen, B. A., Mathur, P., McCradden, M. D., Morgan, L., Ordish, J., Rogers, C., Saria, S., Ting, D. S. W., Watkinson, P., Weber, W., Wheatstone, P., McCulloch, P., DECIDE-AI expert group. (2022). Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Nature Medicine*, 28(5), 924-933. <https://doi.org/10.1038/s41591-022-01772-9>

Zhang, X., Han, J. Y., Heo, J., Ko, J., Yi, W. J., & Song, I. S. (2026). A narrative review of artificial intelligence in dental imaging: From dataset design to clinical translation. *Oral Radiology*, 42(4), 888-900. <https://doi.org/10.1007/s11282-026-00968-w>

Ziaei, S., Samani, D., Behjati, M., Ravari, A. O., Salimi, Y., Ahmadi, S., Rajaei, S., Alimohammadi, F., Raji, S., Deravi, N., & Fakhimi, H. (2025). Accuracy of artificial intelligence in orthodontic extraction treatment planning: A systematic review and meta analysis. *BMC Oral Health*, 25(1), 1576. <https://doi.org/10.1186/s12903-025-06880-9>