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Manufacturing-Structure-Performance Engineering of Advanced Dental Materials: Additive Manufacturing, Surface Engineering and Computational Design

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ABSTRACT

Advanced dental materials are manufactured states whose performance depends on digital geometry, additive or subtractive processing, post-processing, surface modification, defects and oral loading. This focused critical review synthesizes 50 peer-reviewed publications from 2025–2026 using an explicitly documented search, eligibility, screening and evidence-coding protocol rather than a PRISMA systematic-review claim. The literature is integrated through a manufacturing–structure–performance (MSP) framework linking process variables to defect/microstructural and surface states and then to dimensional accuracy, fatigue, wear, adhesion and functional durability. Comparative synthesis shows that additive-manufacturing studies are strongest in static mechanical and accuracy characterization but weaker in defect-informed fatigue; surface-engineering evidence is increasingly multifunctional but coating durability is inconsistently tested; finite-element analysis is advancing toward patient-specific models but remains limited by idealized properties, contacts and experimental validation; and AI/ML is constrained by small, heterogeneous and weakly transferable datasets. A closed digital thread is proposed in which metrology and experiments calibrate predictive mechanics, validated simulations and tests generate traceable datasets, surrogate models accelerate prediction and multi-objective optimization identifies robust process/design windows. Priority directions include defect-informed zirconia AM, cure–conversion–fatigue modelling of printed resins, multifunctional coating durability, experimentally validated patient-specific FEA, inverse implant design, digital twins and sustainability-aware manufacturing optimization.

KEYWORDS *: Advanced dental materials; additive manufacturing; surface engineering; finite element analysis; intelligent optimization.*

NOTATIONS

AI – artificial intelligence; AM – additive manufacturing; CAD/CAM – computer-aided design/computer-aided manufacturing; DIC – digital image correlation; DLP – digital light processing; DOE – design of experiments; FDM/FFF – fused deposition modelling/fused filament fabrication; FEA – finite-element analysis; FTIR – Fourier-transform infrared spectroscopy; ML – machine learning; MOO – multi-objective optimization; MSP – manufacturing–structure–performance; micro-CT – micro-computed tomography; PBF – powder-bed fusion; PEEK – polyetheretherketone; RSM – response-surface methodology; SLA – stereolithography; X – process/material/contact-state vector; E – elastic modulus; K_IC – fracture toughness; H – hardness; P_f – probability of failure; σ_0 – Weibull characteristic strength; m – Weibull modulus; S_L – linear shrinkage; β – regression coefficient; ε – model residual/error term.

INTRODUCTION

Digital dentistry has changed the engineering definition of a dental material. A crown, denture

base, abutment or implant is no longer specified only by chemical composition; it is the output of a digital manufacturing chain that begins with image acquisition and CAD geometry and continues through toolpaths or sliced layers, machine settings, support strategy, thermal or photochemical post-processing, surface finishing and quality control. Each stage can change the final structure and surface state. Consequently, nominally identical material labels can produce different mechanical behavior when the manufacturing histories differ. Contemporary literature therefore needs an engineering framework that treats manufacturing history as part of the material state rather than as an incidental laboratory detail [1, 2].

This distinction is particularly important for additive manufacturing (AM). Layerwise fabrication creates geometric freedom and mass customization but also introduces anisotropy, interlayer interfaces, porosity, stair-step topography, support-related damage, conversion gradients or thermal residual stress depending on the process. For photopolymerized dental resins, orientation and post-curing directly influence final network formation and flexural behavior [3, 4]. For ceramic AM, printing direction, green-part architecture, debinding and sintering determine shrinkage, pore distribution and flaw orientation; recent meta-analyses continue to find that the performance of printed zirconia depends strongly on technology, orientation and layer thickness [5, 6]. Metallic dental components manufactured by powder-bed fusion add a different defect space involving energy density, lack-of-fusion pores, residual stress and rough surfaces that may later be altered by machining, polishing or coatings [7].

Surface engineering then becomes a second manufacturing layer. Polishing, air abrasion, laser texturing, anodization, acid treatment, hydrothermal processing, plasma spraying and multifunctional coatings are applied to change roughness, chemistry, wettability, bioactivity or antibacterial function. From a Mechanical Engineering standpoint, the surface cannot be optimized only for biological response because the same treatment can alter crack population, coating adhesion, friction, wear, corrosion and fatigue. Recent reviews of titanium and zirconia implant surfaces emphasize the increasing complexity of hierarchical micro/nano topographies and smart coatings, while experimental crown studies demonstrate the direct trade-off between functional coating, fatigue life and antagonist wear [8, 9, 10, 11].

Computational mechanics has developed in parallel. Finite-element analysis (FEA) is now widely used to explore implant geometry, framework stiffness, abutment design, contact and load transfer. Yet the value of a model depends on geometry fidelity, constitutive assumptions, contact definition, preload, loading spectrum, mesh convergence and validation. A 2026 systematic review of 278 implant FEA studies concluded that realism-enhancing practices such as patient-specific anatomy, anisotropic bone, nonlinear behavior, dynamic loading, fatigue, remodeling and uncertainty quantification remain incompletely adopted [12]. This means that a visually sophisticated FEA model can still be scientifically weak if its assumptions are unmeasured or its outputs are not validated against experiment.

Artificial intelligence (AI) creates a route to overcome some of these limits, especially when the objective is optimization rather than explanation. Machine-learning surrogate models can learn the input-output relation of thousands of simulations and provide predictions in seconds; finite-element-based machine learning has already been used to optimize complete-arch implant-supported prosthetic configurations [13]. In 2026, surrogate-assisted inverse design and time-resolved FEA-deep-learning frameworks further demonstrated the possibility of near-real-time patient-specific implant analysis [14, 15]. However, speed does not remove the need for validation. A fast surrogate reproduces the bias of the simulations and experiments used to train it; data quality, domain coverage and uncertainty therefore become engineering variables.

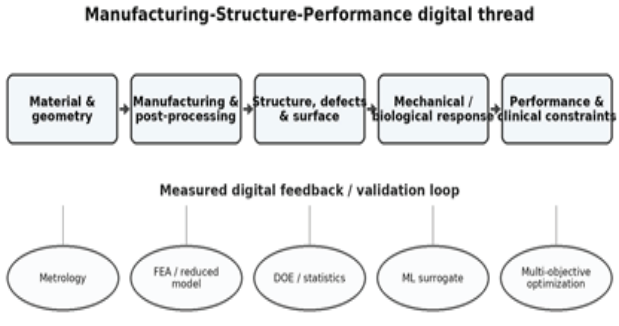


Fig. 1. Integrated manufacturing-structure-performance

digital thread linking measured state variables with FEA, data-driven prediction and optimization

This review is organized around the manufacturing–structure–performance (MSP) relationship. A controllable manufacturing or surface parameter changes the produced material state; that state alters mechanical, dimensional, tribological or biological response; and the response determines component performance. The central gap is that these links are usually studied in separate literatures—additive manufacturing, surface modification, computational mechanics and AI/ML—so a process improvement is rarely traced through measured structure to validated component-level performance. The review therefore contributes: (i) a transparent focused-review protocol for the 50-paper corpus; (ii) a common MSP causal framework for critical comparison; (iii) explicit appraisal of dataset heterogeneity, fatigue evidence, coating durability, model validation and AI/ML generalizability; and (iv) a closed-loop engineering architecture connecting metrology, FEA, surrogate prediction and robust multi-objective optimization. Fig. 1 summarizes the framework used throughout the manuscript.

REVIEW DESIGN, STUDY SELECTION AND EVIDENCE SYNTHESIS

Review scope, information sources and search strategy

The review was designed as a focused critical review, not a PRISMA systematic review or meta-analysis. To make evidence assembly auditable, the revised protocol specifies information sources, search concepts, eligibility rules and synthesis logic. Searches were structured around Scopus, Web of Science Core Collection, PubMed/MEDLINE, ScienceDirect and Google Scholar because these sources jointly cover dentistry, biomaterials, mechanical engineering, additive manufacturing and computational design. Boolean concepts combined (dental OR dentistry OR crown OR denture OR implant OR prosth*) with (additive manufactur* OR 3D print* OR CAD/CAM OR milling OR zirconia OR resin OR PEEK OR titanium OR cobalt-chromium) and, when relevant, (surface engineer* OR coating OR laser OR fatigue OR wear OR finite element OR FEA OR machine learning OR artificial intelligence OR optimization). Searches were restricted to peer-reviewed publications from 2025–2026 and supplemented by backward/forward citation checking.

Eligibility, screening and rationale for the 50-paper corpus

Studies were eligible when they addressed dental materials or dental components and reported, synthesized or modelled at least one explicit engineering link among manufacturing route/parameter, defect or microstructural state, surface condition, mechanical or dimensional response, FEA, AI/ML or optimization. Experimental studies, systematic reviews, meta-analyses, narrative reviews and computational studies were admissible. Exclusion criteria were non-dental applications without a transferable dental-material context, purely clinical reports without engineering variables, editorials/abstracts or non-peer-reviewed items, duplicate datasets without additional evidence, and papers with insufficient methods or inaccessible full text. Screening proceeded from deduplication to title/abstract relevance and then full-text eligibility.

The final corpus contains exactly 50 publications—25 from 2025 and 25 from 2026. This was a purposive quota-balanced design intended to provide a near-current two-year snapshot while preventing one publication year from dominating the comparison. The number 50 is therefore a depth–breadth design choice, not a claim of exhaustive capture: it enabled full-text coding of every included publication across manufacturing, structure/surface state, performance, validation and computation. Older foundational concepts are used as background but are not counted. Because the original focused search was not prospectively registered as PRISMA, intermediate attrition counts were not retained and are not reconstructed retrospectively.

Data extraction, evidence appraisal and synthesis

Each publication was coded using a common MSP template: material/component; manufacturing or surface route; controllable variables; measured defect/microstructure/surface descriptors; performance endpoints; aging/fatigue conditions; computational method; validation strategy; uncertainty/statistical treatment; and stated limitations. Evidence quality was interpreted through five engineering adequacy

dimensions—process-metadata completeness, service-relevant fatigue/aging, independent validation, dataset comparability/traceability and external generalizability. Because the corpus mixes experiments, reviews and computational studies, these dimensions were used for qualitative theme-level appraisal rather than a single numerical risk-of-bias score.

Synthesis was causal rather than specialty-based. Findings were mapped from process or surface input to produced state and then to performance. Conflicting results were interpreted by examining differences in material system, machine/process metadata, post-processing, specimen geometry, aging, test method and model assumptions. Numerical pooling was avoided when datasets were not sufficiently homogeneous. Fig. 2 summarizes the selection and coding workflow; Table 2 provides the corresponding evidence-synthesis matrix.



Fig. 2. Study-selection and evidence-synthesis workflow for the focused 2025–2026 critical review

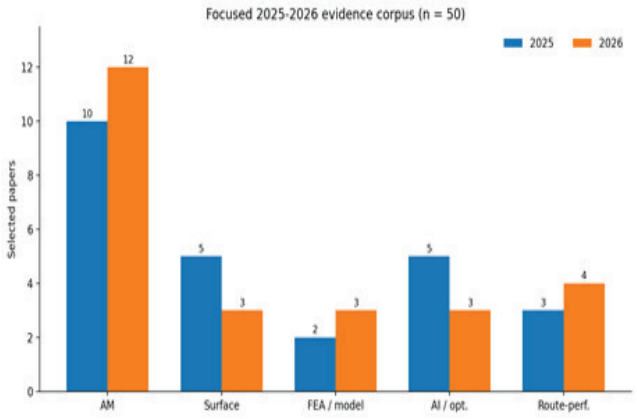


Fig. 3. Distribution of the focused 50-paper evidence corpus by engineering theme and publication year

Table 1. Engineering taxonomy of advanced dental material systems

Material system	Manufacturing state / risk	High-value engineering response
Zirconia / ceramics	Orientation, layer, sintering; pores, flaw direction, residual stress	Accuracy + Weibull/fatigue + fracture-origin mapping
Definitive / denture resins	Exposure/post-cure, conversion gradients, anisotropy, water ageing	Conversion + fit + fatigue/creep + ageing
PEEK / high-performance polymers	Raster/tool condition, crystallinity, fusion and surface energy	Wear + modulus + bonding + fatigue
Ti / Co-Cr alloys	PBF/machining; porosity, residual stress, roughness, passive film	Fatigue + tribocorrosion + dimensional accuracy
Surface-engineered systems	Laser/blasting/anodization/coatings; adhesion and oxide integrity	Adhesion + fatigue + wear/corrosion + biofunction
Patient-specific digital systems	Geometry, mesh, contact, load, material maps and uncertainty	Validated prediction + optimized design window

Table 2. Evidence-synthesis matrix for the 50 included publications

Theme / refs.	Critical synthesis / limitation
AM resins [3,4,21–27,45–47]	Orientation, post-cure and aging effects are consistent; resin/printer/protocol heterogeneity limits transfer.
Ceramic/zirconia AM [5,6,19,28–30,48]	Layer, orientation and firing affect accuracy/strength; defect-resolved fatigue remains sparse.
Metal/PEEK/routes [7,18,20,42]	Route alters surface integrity/durability; process metadata and coupled fatigue evidence are inconsistent.
Surface [8–11,31–34]	Multifunctional surfaces advance faster than adhesion and long-term wear/corrosion validation.
FEA [12,35–38]	Realistic contacts, patient-specific inputs, fatigue, uncertainty and independent validation remain incomplete.
AI/ML [13–15,39–41,43,49]	Speed gains are clear; small heterogeneous datasets and limited external testing restrict generalizability.

MANUFACTURING–STRUCTURE–PERFORMANCE ENGINEERING FRAMEWORK

Digital geometry and competing manufacturing routes

A manufacturing study begins before material is deposited or milled. Image segmentation, CAD

smoothing, mesh or tessellation tolerance, crown cement space, connector geometry, implant thread representation and support placement all influence the final geometry. These variables are often treated as software settings rather than manufacturing inputs, yet they determine wall thickness, local curvature, support accessibility and the direction of principal stresses relative to print layers. Shujaat and Jacobs [16] documented the large diversity of dental printers and technologies now reported in the evidence base, reinforcing the need to record machine and software details as traceable manufacturing metadata rather than generic labels such as '3D printed'.

For fixed dental prostheses, layer thickness and build orientation also change geometric fidelity through discretization and stair-stepping. Abdelhady et al. [17] synthesized evidence showing that layer thickness and orientation materially affect marginal and internal fit. The engineering lesson is broader than the specific numerical recommendations of any one review: dimensional accuracy is a response surface controlled jointly by layer, orientation, geometry and process capability. Therefore, a thesis that optimizes strength while ignoring fit can select an unusable process window; accuracy must be treated as a co-objective or constraint.

Additive and subtractive manufacturing do not simply produce different costs or lead times; they create different defect populations. Subtractive machining begins with a consolidated blank and introduces damage through tool contact, chipping, local heating, residual stress and edge geometry. Additive processes build the part from a liquid, slurry, filament or powder and introduce layer-related interfaces, pores, orientation effects and post-process distortion. Sari et al. [18] and Schettini et al. [7] provide useful route comparisons for implant-abutment and Co-Cr systems, while Pinelli et al. [19] and Ruggiero et al. [6] synthesize the printed-versus-milled zirconia evidence. The correct research question is therefore not 'Is AM better than milling?' but 'Under which process window does the AM defect population become comparable to or better than the damage introduced by the subtractive route for the required response?'

The same logic applies to CAD/CAM milling protocols. Pilecco et al. [20] showed that milling protocol can change fatigue behavior of restorative materials. Tool wear, feed, spindle speed, coolant, bur geometry and machining path should therefore be regarded as controlled variables in high-quality comparative research. For very brittle or thin components, edge damage and sub-surface flaws may dominate fatigue even when average surface roughness appears acceptable. Mechanical Engineering methods such as tool-life monitoring, acoustic emission, 3D surface metrology and residual stress measurement can bring needed rigor to dental machining studies.

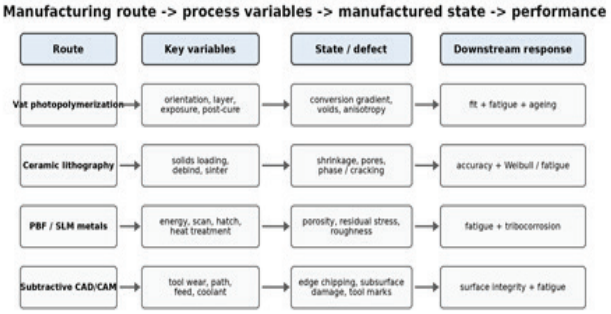


Fig. 4. Manufacturing-route/process-variable map linking additive and subtractive routes to characteristic defects and downstream performance.

Additive manufacturing of resins, ceramics, metals and high-performance polymers

Vat photopolymerization dominates many current dental AM applications because it can produce fine features with relatively high throughput. In DLP, SLA and LCD-type systems, final properties depend on optical exposure and chemistry as much as on geometric resolution. The printed 'green' network is typically incomplete and must be washed and post-cured. Polymerization continues during post-curing, increasing conversion and stiffness but also changing residual stress, dimensions and potentially brittleness. Rizzante et al. [3] and Korkmaz et al. [21] show why post-curing device, time and method should be recorded and optimized rather than treated as a fixed manufacturer instruction.

Build orientation changes the relation between the interlayer architecture and the applied stress. Mudhaffer et al. [4] reported orientation- and aging-dependent changes in flexural behavior of restorative resins,

while Alhotan et al. [22] and Terán Lozada et al. [23] demonstrate material-dependent physicomechanical performance of definitive printed systems. For Mechanical Engineering, orientation should be handled as an anisotropy problem. The research program should quantify whether the material can be represented by an orthotropic elastic/fatigue model, whether anisotropy decreases after post-curing, and whether crack paths align with layer boundaries or local porosity.

Denture-base resins add impact, water uptake, dimensional stability and surface/biological requirements. Coldea et al. [24] and Artopoulou et al. [25] show large material-to-material variability, and Abozaid et al. [26] emphasize that mechanical, optical, biological and clinical behavior should be considered together. High-impact formulations must also demonstrate retention of properties after thermomechanical aging rather than only higher initial strength [27]. A strong PhD therefore links formulation/process variables to network conversion, fracture surface, ageing kinetics and impact/fatigue response.

Ceramic AM is more complex because the printed geometry is not the final geometry. Slurry-based or lithography-based printing produces a green part that undergoes debinding and sintering; both steps introduce substantial shrinkage and can amplify density gradients, support effects and thermal distortion. Alghauli et al. [5] found a consistent influence of print orientation on the physico-mechanical behavior and accuracy of dental ceramics, and Ruggiero et al. [6] confirmed that build direction, technology and layer thickness affect the comparison between additive and subtractive zirconia. The manufacturing problem is therefore multiphysics: optical curing creates the green architecture, then thermal processing determines the final microstructure and residual defect state.

A defect-informed approach should measure density, pore size/orientation and surface flaw distribution in addition to flexural strength. Pinelli et al. [19] highlights the value of Weibull statistics when comparing printed and milled zirconia, while Sabatini et al. [28] links firing and build orientation to flexural and structural behavior. Bergler et al. [29] further indicates that mono- and multilayer zirconia should not be treated as equivalent because layer chemistry and microstructure may alter the response. For multilayer materials, the position of each layer relative to the tensile field becomes a design variable, motivating layer-resolved microhardness, phase, grain and fracture-origin mapping [30].

The scalar shrinkage value is not sufficient when shrinkage is anisotropic. A research-grade study should obtain Sx, Sy and Sz, quantify shape distortion with 3D scanning, and correlate the tensor-like shrinkage response with print orientation, support configuration, layer thickness, sintering schedule and local solid loading. Such a dataset can feed compensation algorithms that pre-deform CAD geometry to reduce final error.

Powder-bed fusion of Ti and Co-Cr enables customized frameworks, porous implants and complex geometries that are difficult to machine. However, the process introduces rough as-built surfaces, residual stress and internal pores that strongly affect fatigue. Schettini et al. [7] provides a direct manufacturing-route comparison for Co-Cr alloys. The next research step is to connect energy input and scan strategy to pore morphology, residual stress and fatigue using micro-CT, metallography and fracture mechanics rather than reporting only yield strength or hardness. Surface finishing should be treated as part of the final route because it can remove critical near-surface flaws while simultaneously altering dimensions.

PEEK and related polymers occupy a special position because their lower modulus can modify load transfer compared with metal or ceramic components. Their performance depends on both bulk processing and surface treatment for bonding. Sari et al. [18] compared additively/subtractively manufactured zirconia and PEEK implant abutments after thermomechanical aging, showing why manufacturing route and component connection must be considered together. A Mechanical Engineering contribution could combine polymer processing, crystallinity and surface treatment with wear/fatigue and validated contact mechanics.

$$S_L = [(L_0 - L_f)/L_0] \times 100\% \quad (1)$$

Table 3. Additive-manufacturing variables that should be controlled and reported

AM route	Mandatory process metadata	Recommended response set
SLA/DLP/LCD	Machine, wavelength, layer, orientation, exposure, support, wash, post-cure	Fit + conversion + anisotropic flexure/fatigue + ageing
Ceramic lithography	Solids loading, orientation, layer, debind, sinter, support	3D shrinkage + density + microstructure + Weibull/fatigue
FDM/FFF	Nozzle/bed temperature, raster, infill, speed, chamber/cooling	Density + DMA/DSC + orthotropic mechanics + wear/fatigue
PBF/SLM/DMLS	Power, scan speed, hatch, layer, build direction, heat treatment	micro-CT + residual stress + fatigue + tribocorrosion + accuracy
Hybrid AM + machining	AM history, stock allowance, toolpath and finishing	Surface integrity + dimensional accuracy + residual fatigue

RESULTS AND DISCUSSION

Process-structure-property-performance relationships

The performance of an additively manufactured part is often governed by the largest critically oriented defect rather than average porosity. A pore that is harmless in compression may become critical when placed near a tensile surface or connector. Therefore, density alone is an incomplete quality metric. Defect characterization should include size distribution, sphericity, orientation, distance from surface and relationship to the principal stress field. micro-CT provides a non-destructive route to build this descriptor and can be registered directly to a finite-element mesh to create defect-informed models.

Where Pf is probability of failure, sigma0 is characteristic strength and m is the Weibull modulus. The value of m should not be interpreted as a universal material constant because specimen geometry, surface finish and process state change the active flaw population. Pinelli et al. [19], Ruggiero et al. [6] and Bergler et al. [29] collectively motivate a process-specific reliability map in which orientation, layer and sintering are independent variables and m, sigma0, density and critical flaw size are responses.

In printed resins, the analogous hidden state variable is polymer network development. Degree of conversion, crosslink density, residual monomer and water uptake control stiffness, strength, creep, wear and biocompatibility. Because post-curing is spatially dependent on light penetration and geometry, a single surface measurement may not represent the interior. FTIR or Raman measurements at multiple depths, combined with microhardness or nanoindentation, can identify conversion gradients. Rizzante et al. [3] and Korkmaz et al. [21] show that post-curing conditions change final properties; the next step is to identify a process law that predicts properties from energy dose and thermal history.

where Y may be conversion, flexural strength, water sorption or fatigue life and Xi are process variables such as orientation, layer, exposure and post-cure time. The equation is not a substitute for mechanism; its value is to reveal interactions and identify regions for mechanistic follow-up. A good PhD uses DOE/RSM to reduce the design space, then uses microscopy, spectroscopy or FEA to explain why the optimum occurs.

Surface roughness is often reported as Ra or Sa, yet identical average roughness can conceal different sharpness, spacing, directionality and defect morphology. A polished sinusoidal-like surface and an air-abraded surface can have similar Ra but very different stress concentration, wettability and antagonist interaction. For advanced surface studies, 3D parameters such as Sa, Sq, Ssk, Sku, peak density and developed interfacial area are more informative. The surface should also be imaged and its functional response measured through friction, wear, contact angle, coating adhesion or corrosion rather than treated as a purely geometric descriptor.

This is particularly important for zirconia bonding treatments and implant coatings. Cantelli et al. [31] show that surface treatment influences fatigue survival of bonded zirconia, while da Silva et al. [9] demonstrates that an antimicrobial glass coating can change fatigue life and antagonist wear. These studies illustrate why surface engineering requires simultaneous evaluation of intended function and mechanical side effects.

$$P_f = 1 - \exp[-(\sigma/\sigma_0)\text{^}m] \quad (2)$$

$$Y = \beta_0 + \Sigma\beta_i X_i + \Sigma\beta_{ii} X_i^2 + \Sigma\beta_{ij} X_i X_j + \varepsilon \quad (3)$$

Surface engineering, accuracy and multifunctional interfaces

Research gap and contribution. Surface-engineering literature is rich in novel treatments but comparatively weak in coupled durability evidence. Initial wettability, antibacterial response or bond strength is frequently reported without demonstrating that the modified interface survives fatigue, wear, corrosion and aging.

The MSP framework therefore treats surface state as a manufactured interface whose functional benefit must be co-validated with adhesion and mechanical durability.

The engineering objective of a dental surface is not simply to make it rough or smooth. Implant surfaces must support initial stability, osseointegration, soft-tissue response and resistance to microbial colonization while retaining corrosion and fatigue integrity. Restorative surfaces must balance esthetics, antagonist wear, polishability, bonding and crack resistance. Surface engineering is therefore a multi-objective problem in which an intervention can improve one response while degrading another.

Recent reviews classify implant surface modification into subtractive treatments, physicochemical activation, laser processing, anodization and coating-based approaches. Aissi et al. [8], Abdo et al. [32], Cheng et al. [33], Jadhav et al. [11] and Balang et al. [10] collectively show a trend from conventional microroughening toward hierarchical micro/nano structures, bioactive chemistry, antibacterial function and local drug delivery. From an engineering perspective, every added layer creates an interface; therefore, coating adhesion, residual stress, crack resistance and stability under cyclic contact, sterilization and corrosion are essential translation metrics.

Laser surface engineering is attractive because texture can be created without adding a foreign coating, while process parameters can be digitally controlled. However, fluence, pulse duration, scanning overlap and thermal accumulation can change roughness, oxide chemistry and residual stress. A research program should identify a processing window that improves wetting or cell-relevant topography without inducing microcracking or fatigue reduction. Similar logic applies to blasting and acid etching: the treatment should be characterized by the resulting state variables rather than only by the nominal protocol.

Coatings introduce additional design dimensions: material selection, thickness, porosity, elastic modulus, adhesion, thermal expansion mismatch and dissolution rate. A thin hard coating can improve wear but may delaminate under bending; a bioactive layer can accelerate interface response but may be mechanically weak; an antimicrobial coating can lose function after wear. Pytel et al. [34] further adds manufacturing sustainability to this problem, highlighting energy and environmental indicators as future selection criteria.

Dental manufacturing differs from many engineering applications because a component can be mechanically strong yet clinically unusable if its fit is poor. Accuracy must therefore be incorporated into process optimization as a response or constraint. Printed fixed prostheses exhibit errors from pixel/voxel resolution, layer thickness, orientation, support, resin shrinkage and post-curing. Ceramic parts add sintering shrinkage; metal PBF adds thermal distortion; subtractive machining adds tool radius and access limitations. Abdelhady et al. [17] provides a current synthesis of layer-thickness and build-orientation effects on fit, while Shujaat and Jacobs [16] highlights the breadth of printer technologies and the need for evidence-based machine selection.

Dimensional verification should ideally use a full-field deviation map rather than a few marginal measurements. The process can be represented as: nominal CAD -> printed/milled part scan -> registration -> signed deviation field. This field can be decomposed into global scale error, warpage, local support distortion and surface stair-step. For ceramic AM, pre-sinter and post-sinter scans can isolate thermal shrinkage from printing error. Such data can be used to create machine/process-specific compensation factors or geometry morphing algorithms.

A high-value engineering objective is to optimize the Pareto trade-off among accuracy, strength and production time. Thinner layers may improve accuracy but increase build time; orientations that reduce supports may change mechanical anisotropy; aggressive post-processing may improve surface quality but remove dimensional stock. The result should be a process window rather than a single 'best' setting.

Table 4. Surface-engineering routes and validation requirements

Route	Primary mechanical risk	Minimum validation set
Polishing / grinding	Subsurface flaws; phase/residual-stress change	3D roughness + SEM + fatigue/wear
Air abrasion / etching	Sharp flaws, contamination, strength reduction	Surface damage + bond fatigue + fractography
Laser texturing	Thermal damage, microcracks, residual stress	Topography + chemistry + residual stress + fatigue
Anodization / activation	Brittle/porous oxide; altered corrosion	Oxide thickness + adhesion + electrochemistry + fatigue
Bioactive / smart coating	Delamination, mismatch, dissolution or wear loss	Adhesion + cyclic shear + corrosion/ageing + function/safety

Predictive finite-element mechanics and validation

Research gap and contribution. Dental FEA has progressed faster in geometric sophistication than in parameter and validation fidelity. The key gap is weak transfer of measured manufacturing state—anisotropy, porosity, residual stress, surface/interface behavior and as-built geometry—into model inputs. The framework therefore defines model fidelity through measurable state variables, sensitivity analysis and independent experimental validation rather than visual complexity.

FEA is most valuable when it tests a defined mechanical hypothesis. For example, if a new implant thread is intended to reduce cortical stress, the model should isolate geometry while maintaining comparable material and contact assumptions. If a printed polymer framework is proposed to alter load transfer, measured anisotropic properties should be used. Poovarodom et al. [35] and Sahin Hazir et al. [36] demonstrate how material choices change stress distribution, but broader review evidence indicates that many dental FEA studies still rely on isotropic linear properties, perfect interfaces and static loads [12, 37].

Model fidelity can be organized as a ladder rather than an all-or-nothing choice. Level 1 uses simplified geometry and linear elastic static analysis to understand trends. Level 2 introduces anatomical geometry, mesh convergence and realistic contact. Level 3 adds preload, friction, nonlinearities and oblique/dynamic load. Level 4 adds fatigue, remodeling, patient-specific material maps and uncertainty. Level 5 combines experimental validation with surrogate or digital-twin functionality. Fig. 5 emphasizes that higher complexity is only meaningful when parameters can be justified or measured.

Implant systems contain multiple contacts: crown-abutment, abutment-implant, screw threads and bone-implant interface. Treating all contacts as perfectly bonded eliminates slip and can underestimate local stress concentration. Screw preload changes the normal force and frictional capacity of the joint. Similarly, osseointegration is not binary during healing; interfacial stiffness evolves with time. A model intended to predict mechanical complications should therefore justify contact, friction and preload, perform sensitivity analysis, and report how results change when interface assumptions are varied.

Padullés-Roig et al. [38] is particularly instructive because fatigue testing and FEA are combined around a clinically motivated geometry change. This experiment-simulation combination is preferable to isolated FEA because the model can be challenged against component behavior. A validation metric can include strain-field error, displacement, stiffness, load-to-failure or failure location. Agreement in a single scalar stress is not validation because stress is not directly measured in most laboratory setups.

The next generation of dental FEA should include manufacturing state variables. For printed zirconia or metals, micro-CT-derived pores can be imported or represented statistically. For printed polymers, orthotropic properties can be assigned by build direction. For multilayer zirconia, layer-specific elastic/fracture properties can be mapped spatially. For surface coatings, cohesive-zone interfaces can simulate delamination. These approaches convert FEA from a geometry-only tool into a process-aware model.

where K depends on displacement u and a set of material, contact and process-state variables X. In linear models K is constant; in nonlinear contact, damage or material models it evolves. The research challenge is to identify which components of X materially affect the clinical/mechanical response and then measure them. This sensitivity-driven approach prevents unnecessary model complexity while improving predictive value.

$$[K(u, X)]\{u\} = \{F\} \quad (4)$$

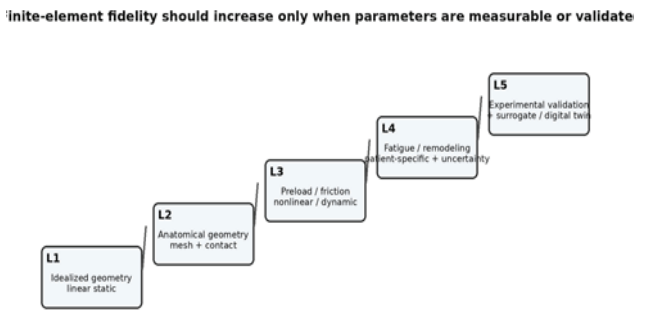


Fig. 5. Finite-element fidelity ladder from idealized screening analysis to validated patient-specific digital twins.

Table 5. Minimum reporting and validation checklist for dental finite-element studies

Domain	Minimum requirement	Preferred advanced practice
Geometry / mesh	Source, simplification, element type, size, convergence	Patient-specific scan + dimensional verification + adaptive refinement
Materials	E, nu and source	Measured anisotropic/nonlinear/viscoelastic process-specific data
Contact	Bonded/frictional definition	Measured friction, preload and interface law + sensitivity
Loading	Magnitude, direction and location	Variable/dynamic spectrum and muscle/occlusal constraints
Validation	Comparison with independent data	DIC/strain/displacement/failure-mode validation
Uncertainty	At least sensitivity analysis	Monte Carlo/probabilistic inputs and confidence bounds

Machine learning, surrogate models and digital twins

Research gap and contribution. AI/ML applications demonstrate speed and optimization potential, but generalizability is limited by small datasets, inconsistent metadata, simulation-generated labels and narrow material/machine domains. The proposed contribution is a traceable physics–data workflow in which domain coverage, external testing, uncertainty and high-fidelity confirmation are mandatory before optimization claims are accepted.

Design of experiments remains the most appropriate starting point when data are limited and factors are controllable. Full/fractional factorial designs, Taguchi arrays, central-composite designs and Box-Behnken designs can identify main effects and interactions. RSM provides interpretable polynomial models, but high-dimensional nonlinear relationships may require random forests, gradient boosting, Gaussian processes or neural networks. The key transition is from a statistical fit to a validated surrogate capable of predicting unseen combinations within a defined domain.

In manufacturing, surrogate modelling is valuable because both experiments and high-fidelity FEA are expensive. Mohammadnabi et al. [39], Shangguan et al. [40] and Soori et al. [41] describe AI applications across material development, parameter optimization, monitoring and post-processing. Dental research can use the same architecture: generate a structured dataset from DOE-guided experiments and calibrated simulations, train a surrogate, quantify its error and uncertainty, then use the surrogate in an optimizer. The original experiment/FEA must remain the ground truth for final validation.

Dental implant design provides one of the clearest current demonstrations of this approach. Chen et al. [13] generated a large FEA dataset, trained an artificial neural network and used particle swarm optimization to identify improved complete-arch implant configurations with near-real-time computation. Prados-Privado [14] extended the concept toward numerical inverse design using neural surrogates and evolutionary optimization. These studies suggest a future in which patient geometry and bone quality become inputs to an optimization engine rather than being assessed through a small set of manually selected implant designs.

The attraction of surrogate models is computational speed, but three controls are essential: (1) the training domain must cover the intended design space; (2) an independent test set must quantify generalization; and (3) optimized solutions must be re-evaluated with high-fidelity FEA and preferably experiment. Extrapolation beyond the training domain should be explicitly rejected or associated with high uncertainty.

A digital twin differs from a static FEA model because it is intended to update as the physical system or process changes. In dental implants, healing changes bone-implant contact and interfacial stiffness. Rodriguez-Molinero and Prados-Privado [15] combined FEA-derived states, osseointegration dynamics and deep learning to produce time-resolved biomechanical predictions. The study is a proof-of-concept and still requires patient-specific biological validation, but it establishes a useful research architecture: physics-based simulation generates interpretable states, mechanobiology updates them over time, and a surrogate reduces computation.

A manufacturing digital twin can be constructed similarly. Sensor data from an AM machine (exposure, temperature, layer images, energy, recoater signals) can update a process model; metrology and mechanical tests can update the property model; and optimization can adjust future builds. For dental manufacturing, the biggest barrier is not algorithm availability but standardized, traceable datasets that connect machine settings to final component performance.

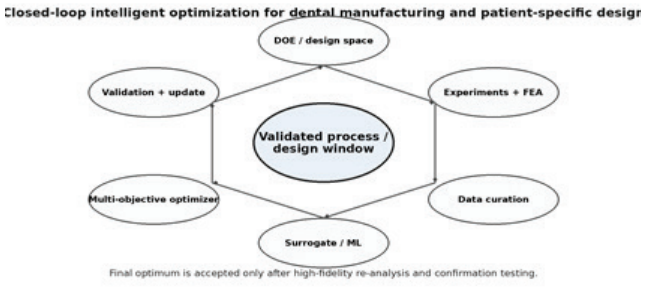


Fig. 6. Closed-loop intelligent optimization architecture for dental manufacturing and patient-specific component design.

4.5 Multi-objective process/design optimization

Most dental-material studies optimize a single response, yet practical design is inherently multi-objective. A zirconia process should maximize reliability and accuracy while minimizing roughness, shrinkage error and production time. A printed resin process must balance strength, fatigue, water sorption, fit, conversion and optical stability. An implant surface should balance osseointegration, antibacterial function, coating adhesion, fatigue and tribocorrosion. A patient-specific implant design must reduce bone stress without creating excessive implant stress or violating surgical constraints.

where x contains material, process, geometry and surface variables. The result is normally a Pareto set rather than one mathematically unique solution. Methods such as NSGA-II, particle swarm optimization, differential evolution, Bayesian optimization and desirability functions can be used depending on the number of variables, computational cost and uncertainty. The objective should not be to use a fashionable optimizer; it should be to produce a physically interpretable process/design window that can be experimentally validated.

Robust optimization is especially important because dental materials exhibit scatter and patient conditions vary. A nominal optimum with extremely steep sensitivity may be undesirable in manufacturing. Process robustness can be quantified by variance, probability of failure or worst-case response across plausible parameter distributions. This transforms a research contribution from 'optimal setting at laboratory conditions' into 'manufacturing window that retains performance under realistic process variability'.

Sustainability can be added as another objective. AM may reduce stock waste but increase photopolymer, support, cleaning and post-curing requirements; surface treatments may consume energy and chemicals; ceramic sintering is energy intensive; milling consumes tools and blanks. Pytel' et al. [34] identifies the shortage of standardized sustainability indicators in dental surface engineering. A future mechanical-engineering research program can combine quality, fatigue, energy, waste and cost in a lifecycle-aware Pareto analysis.

$$\min F(x) = [f_1(x), f_2(x), \ldots, f_k(x)], \text{ subject to } g_j(x) \leq 0 \text{ and } h_l(x) = 0 \quad (5)$$

Advanced composites, functionally graded structures and architected lattices extend the design space beyond homogeneous material selection. The source review emphasizes that filler architecture, multimaterial interfaces, designed porosity and spatial gradients should be measured in the as-manufactured state, then linked to anisotropic constitutive behaviour, fatigue and failure location. Sustainability and process economics should be treated as quantified co-objectives rather than assumed advantages of additive manufacturing; measurable inputs include material waste, energy, post-processing, tool consumption, rejected components and validated service performance [40, 41].

Advanced composites and hybrid dental materials

Advanced dental composites should be treated as hierarchical engineered systems rather than mixtures described only by matrix and filler percentages. Polymer chemistry controls conversion, viscoelasticity and water uptake; filler morphology governs stiffness, crack deflection and polishing response; interfaces determine load transfer and hydrolytic stability; and the manufacturing route controls filler orientation, voids, cure gradients and surface texture. Recent 3D-printing literature illustrates this coupling because nominally similar photopolymer systems can exhibit different flexural response, aging sensitivity and dimensional behavior after changes in orientation and post-curing [4, 3, 23]. A Mechanical Engineering review should therefore describe a composite by a state vector that includes composition, filler architecture, conversion, porosity, residual stress and surface condition, not by commercial class alone.

For particulate and nanofilled systems, the key design issue is the competition between reinforcement and defect creation. Increasing filler fraction can raise modulus and hardness but can also increase viscosity, limit printability, promote agglomeration and create stress concentrations if interfacial bonding is poor. For short- or continuous-fibre systems, fibre length, orientation, volume fraction and interface quality produce strong anisotropy that can be beneficial when aligned with functional load paths and harmful when the clinical load rotates relative to the build direction. This suggests a PhD pathway based on processing-induced architecture: quantify local reinforcement orientation by microscopy or micro-CT, derive orthotropic constitutive properties, and validate component-level FEA under axial and oblique loading.

Hybrid material systems also create interfaces between materials with different elastic modulus, thermal expansion, fracture behavior and water sorption. Such interfaces can redistribute stress or become preferential crack paths. The correct research question is therefore not whether a hybrid material is 'stronger', but whether the interface remains stable under combined thermal, moisture and cyclic mechanical exposure. A useful experimental program can combine lap/shear or interfacial fracture tests, thermocycling, cyclic loading and fractography, then use cohesive-zone modelling to convert observed interface degradation into predictive component simulations.

Machine learning is attractive for composition development because the variable space can include resin chemistry, filler type, particle size, silanization, fraction, print settings and cure schedule. However, data-centric material discovery requires disciplined metadata and physically meaningful descriptors. Shangguan et al. [40] and Mohammadnabi et al. [39] emphasize the broader potential of AI in additive material/process development; for dental materials, the next step is to create compact but high-quality datasets where each formulation is linked to rheology or printability, conversion, defect state, mechanical response and aging. Physics-informed descriptors such as filler surface area, modulus contrast, cure dose and porosity are more transferable than one-hot commercial-material labels.

Functionally graded and multimaterial structures

Natural teeth are functionally graded: enamel, dentin and the dentino-enamel junction create spatial variations in modulus, toughness and crack resistance. Most manufactured restorations and implants remain comparatively homogeneous, producing abrupt stiffness transitions at cement, abutment, bone or veneering interfaces. Functionally graded materials (FGMs) offer a Mechanical Engineering strategy in which composition, porosity, phase fraction or architecture varies continuously or stepwise with position. The design target is not simply a high bulk strength; it is a controlled spatial property field E(x), K_IC(x), hardness H(x) or porosity p(x) that manages contact stress, protects interfaces and directs damage away from critical regions.

In a crown, a graded ceramic/polymer or ceramic-composition architecture could combine a hard wear-resistant occlusal surface with a more compliant interior that reduces tensile stress at the cement interface. In an implant, a dense high-strength core may transition to a porous or bioactive outer zone to reduce effective stiffness and improve bone ingrowth. In a framework, topology and material grading can be coupled so that local stiffness is concentrated along load paths while non-critical volume is reduced. These concepts align naturally with additive manufacturing, which can control geometry layer-by-layer and, in selected platforms, vary material or energy input spatially.

The main research barriers are manufacturability and verification. A designed gradient is not necessarily the gradient that is produced after photopolymerization, debinding, sintering, thermal shrinkage or multi-material bonding. Therefore, a defensible PhD should distinguish intended digital gradient, manufactured gradient and effective mechanical gradient. Micro-CT, microscopy, spectroscopy or nanoindentation maps can characterize the actual spatial state; FEA should then use the measured rather than nominal property distribution. The resulting model can answer whether a gradient genuinely reduces critical stress or simply introduces a new weak transition zone.

Optimization of FGMs is intrinsically multi-objective. Increasing compliance may reduce stress shielding but increase micromotion; increasing surface porosity may

support tissue integration but reduce fatigue strength; adding a tough polymer-rich zone may improve damage tolerance but reduce wear resistance. The design variables can be represented by a small number of gradient-control parameters and optimized using a surrogate-based framework. Validation should include not only peak load but cyclic survival and failure origin, because a graded design is successful only when it changes the mechanism and location of damage in a favorable way.

Porous, lattice and architected implants

Architected materials extend dental design beyond conventional solid geometry. Lattice cells, stochastic porosity and triply periodic minimal surface (TPMS) structures can reduce mass, tune effective elastic modulus and create interconnected pore networks while retaining a load-carrying skeleton. For metallic implants, the principal motivation is stiffness matching and biological integration; for polymeric or hybrid prostheses, lattices can also control compliance, damping and material use. The engineering design space includes unit-cell topology, relative density, strut or wall thickness, pore size, orientation, grading and local reinforcement.

A critical distinction must be made between geometric porosity that is intentionally designed and manufacturing porosity that is an uncontrolled defect. Designed pores can improve functional architecture, whereas lack-of-fusion pores, unmelted particles, trapped resin or ceramic voids can initiate fatigue cracks. Micro-CT is therefore particularly valuable: it can separate intended geometry from defects, quantify strut deviations and provide a mesh for as-manufactured FEA. This closes the process-structure-performance chain and avoids the common assumption that the CAD lattice is identical to the manufactured lattice.

The fatigue problem is central. Lattice structures contain many stress raisers, and their behavior depends on surface roughness, residual stress and build orientation. A static compression test can screen stiffness but cannot establish long-term implant safety. A research study should combine coupon-level cell testing, component-level cyclic loading, fractography and probabilistic modelling. Surface finishing should be included because it can change both roughness and strut dimensions. For coated porous structures, coating penetration, thickness uniformity and local adhesion should be characterized rather than inferred from an external flat specimen.

Computationally, architected structures create an opportunity for multiscale modelling. Homogenized properties can make whole-implant optimization computationally practical, while local submodels resolve critical cells near threads or interfaces. Surrogate models can then explore large topology/relative-density spaces. The optimized design must be checked against manufacturability constraints such as minimum wall thickness, trapped powder/resin removal, support accessibility and post-processing. Thus the true objective is a manufacturable architecture with controlled variability, not an ideal mathematical lattice.

Sustainability and lifecycle-aware optimization

Sustainability should enter dental manufacturing as a measured engineering response rather than a qualitative claim that additive manufacturing is automatically ‘green’. Subtractive manufacturing generates machining chips, partially used blanks and tool wear but often has mature workflows and predictable productivity. Additive manufacturing can reduce geometric material waste, yet it may require supports, failed builds, disposable vats or films, solvent washing, inert gas, post-curing, debinding and high-temperature sintering. The net outcome depends on material class, batch size, equipment utilization and the functional lifetime of the restoration or implant.

A useful lifecycle boundary for a PhD can begin at digital manufacturing and end at a validated component, thereby avoiding unsupported whole-clinic assumptions. Measurable inputs include mass of virgin and discarded material, solvent use, support mass, machine time, electrical energy, furnace energy, tool consumption, post-processing consumables and rejected components. These can be normalized per accepted component and then coupled with quality responses such as fit, strength and fatigue life. A process with low energy per build may be less sustainable if its rejection rate or replacement frequency is high.

Process economics can be analysed in parallel. Cost per accepted part can be decomposed into machine

amortization, material, labor, energy, tooling, post-processing, inspection and scrap. Sensitivity analysis reveals which assumptions dominate. For small-batch patient-specific production, digital flexibility may outweigh raw material efficiency; for standardized high-volume components, throughput and post-processing may dominate. The analysis should therefore report the production scenario explicitly rather than producing a universal ranking.

The most useful final output is a multi-objective Pareto map involving performance, manufacturing time, cost and environmental burden. Pytel' et al. [34] notes the importance of smart and sustainable surface-engineering strategies, while AI/AM reviews describe the possibility of data-driven process control [41, 39]. Combining these themes creates a new doctoral direction: a closed-loop manufacturing system that rejects low-quality states early, reduces unnecessary reprocessing and optimizes a verified performance-to-resource ratio.

Evidence synthesis and research maturity

The focused corpus shows a consistent maturity gradient. AM research is comparatively mature for static mechanical and dimensional characterization but less mature for defect-resolved fatigue, cross-machine transfer and long-term aging. Surface-engineering research increasingly integrates topography, chemistry and biofunction, yet coating adhesion and retained function after cyclic wear/corrosion are less consistently demonstrated. FEA is mature as a comparative hypothesis tool but less mature as a predictive tool when patient-specific properties, realistic contacts, fatigue, uncertainty and experimental validation are absent. AI/ML shows rapid computational progress but the weakest evidence for external generalization because datasets are often small, heterogeneous or simulation-derived.

Evidence quality must therefore be interpreted by the completeness of the causal chain rather than by novelty alone. A statistically significant increase in static strength does not establish fatigue reliability; an antimicrobial coating is not durable unless function is retained after mechanical/environmental exposure; a detailed stress map is not validation; and low internal ML error does not demonstrate transfer to an unseen printer, material or geometry. Table 6 makes these limitations and minimum strengthening actions explicit.

The strongest future studies should connect process parameter → measured state → service-relevant degradation → validated model → uncertainty-aware optimization. Fig. 7 summarizes the qualitative maturity pattern used to derive the translational roadmap in Section 5. The categories are comparative descriptors within this focused corpus and not formal risk-of-bias scores.

Table 6. Evidence-quality limitations and minimum strengthening actions

Theme	Evidence limitation and minimum strengthening action
AM	Heterogeneous machines/materials and static-test dominance; require full metadata, cross-build replication, micro-CT/fractography and aging/fatigue.
Surface	Short-term functional endpoints and underreported durability; co-test adhesion, cyclic wear/tribocorrosion, fatigue and retained function.
FEA	Idealized properties/contacts and inconsistent validation; use measured inputs, sensitivity/convergence and DIC/bench validation.
AI/ML	Small heterogeneous data and external-domain risk; report provenance, independent test performance, uncertainty and re-FEA/experimental confirmation.
Cross-study	Non-standard metadata/endpoints; adopt common MSP state variables and minimum reporting sets.

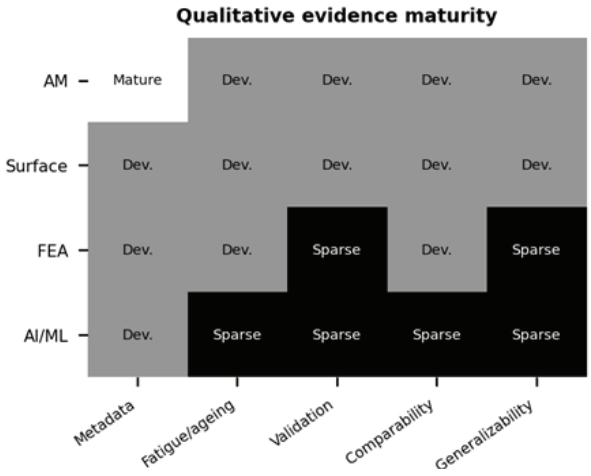


Fig. 7. Qualitative evidence-maturity map for the focused 2025–2026 corpus

RESEARCH GAPS, TRANSLATIONAL ROADMAP AND REPORTING PRIORITIES

A recurring limitation across dental manufacturing is that nominally identical variables do not always describe identical physical states. A label such as 50 µm layer thickness does not specify exposure history, resin age, build temperature, washing efficiency, post-cure irradiance or support-induced distortion. Likewise, a zirconia sintering temperature does not fully describe heating rate, dwell, cooling history, green density or furnace loading. Reproducibility therefore requires measurement of the state produced by the process. For polymers this may include degree of conversion, glass-transition behavior and water uptake; for ceramics, density, phase fraction, grain/defect population and shrinkage; for metals, porosity, residual stress and surface state.

Measurement uncertainty should be separated from material/process variability. A 3D scanner introduces registration and resolution uncertainty; micro-CT thresholding changes measured pore volume; surface roughness depends on filtering and scan area; fatigue life is intrinsically scattered. A research dataset should include repeated specimens, repeated measurements where appropriate and a measurement-system check before optimization. Otherwise, a machine-learning algorithm may model metrology noise as if it were a process mechanism. Statistical reporting should therefore include dispersion and confidence intervals, not only means and p-values.

For optimization, uncertainty should enter the decision variable explicitly. If two process settings have similar mean strength but one has a much larger variance, the robust setting may be preferable. A probability-of-failure criterion, lower confidence bound or tolerance-based objective can be used in addition to mean response. This is especially important for brittle zirconia, where Weibull-type reliability is more informative than an isolated average flexural strength, and for fatigue, where run-outs and censored observations should be retained rather than discarded [19, 6].

Benchmark-quality data also requires traceable metadata. Each specimen should be associated with material batch, machine, build job, position on platform, geometry file/version, process parameters, post-processing, operator-relevant steps, storage, aging, metrology and test condition. The resulting data object becomes useful for both conventional statistics and future ML. This is one reason a carefully designed PhD dataset of hundreds of traceable specimens can be more scientifically valuable than thousands of values extracted from heterogeneous publications.

Dental components do not experience one isolated degradation mode. Polymers absorb water while they are cyclically loaded; ceramics experience contact and slow crack growth in a humid environment; implants undergo micromotion, fretting and electrochemical reactions; coatings experience contact, corrosion and interfacial shear. Yet many laboratory studies isolate a single variable because it simplifies testing. The next research step is not to reproduce the entire mouth indiscriminately, but to identify the dominant coupled damage sequence for the application and reproduce that sequence with controlled boundary conditions.

For printed restorative resins, a useful hierarchy is dry static screening, water-conditioned properties, thermocycling, cyclic loading and then combined thermomechanical exposure. Mudhaffer et al. [4], Alhotan et al. [22] and Alhotan et al. [27] show why aging state matters when interpreting printed polymer performance. The research question should ask which microstructural or network variable changes during aging and whether this variable explains the change in fatigue or fracture. FTIR/Raman, DMA, sorption and fractography can therefore be paired with mechanical testing rather than treating aging as a black-box conditioning step.

For metallic implant surfaces and coatings, electrochemical behavior should be evaluated before, during or after mechanically assisted surface disruption depending on the hypothesis. Tribocorrosion testing can partition material loss conceptually into mechanical, electrochemical and synergistic contributions, while post-test SEM/EDS identifies oxide disruption, debris and coating delamination. The study should then determine whether the damaged state alters fatigue strength or interface behavior. This creates a more clinically meaningful chain than reporting a corrosion curve and a wear scar in unrelated specimens.

Accelerated ageing must also preserve mechanism. Raising temperature or load can shorten test time, but an excessively severe condition may activate a failure mode that is not dominant in service. A sound PhD therefore uses acceleration only after identifying the expected mechanism and includes at least one service-relevant confirmation condition. The strongest output is a validated acceleration rule or damage-equivalence criterion rather than simply a high number of cycles.

A recurring disconnect in dental materials research is the jump from simple coupon tests to claims about clinical components. Coupon specimens are essential for isolating material/process effects, but they remove geometric stress concentrations, cement layers, screw preload, occlusal contact, manufacturing supports and anatomical variability. Conversely, testing only complete crowns or implants makes it difficult to identify which mechanism caused the observed difference. A staged translation ladder resolves this tension.

Stage I should use standard or simple specimens to screen process variables and estimate constitutive, fracture, wear or fatigue parameters. Stage II should use a representative component geometry manufactured by the same process and surface route. Stage III should use experimentally validated FEA to explain local stress/strain and translate measured material behavior into component performance. Stage IV can introduce patient-specific geometry, bone quality or occlusal variability. Stage V, where feasible, should connect the engineering endpoint with dental/biological or clinical evidence through interdisciplinary collaboration. Each stage should have a predefined gate; failure to reproduce the mechanism at a higher stage should trigger model revision rather than selective reporting.

Manufacturing readiness can be assessed similarly. A process demonstrated on one printer and one batch is an exploratory result. Repeating the optimized setting across build positions, days or material lots tests robustness. Repeating on a second machine or laboratory tests transferability. Monitoring build signals and applying statistical process control tests whether the process is controllable. Only after these steps should an ML model be described as deployable or a process window as generalizable. Shujaat and Jacobs [16] emphasize the practical importance of evidence-based printer selection, while Chen and Wei [1] show how dental 3D printing spans very different material/process classes; both reinforce the need to define the domain in which a conclusion is valid.

This ladder also creates a publication strategy. The coupon/process paper can establish mechanism; the component/FEA paper can establish transferability; the optimization paper can establish design value; and the final translational study can establish practical relevance. Such a sequence is more coherent than four unrelated material-comparison papers because each paper reduces a specific uncertainty in the same causal chain.

Digital twins and cross-laboratory AI depend on interoperability. At present, manufacturing data may reside in printer software, geometry in STL/3MF files, metrology in proprietary scan formats, microscopy as images and mechanical results in spreadsheets. A future-ready research program should create a specimen-level identifier that links these sources without losing provenance. A lightweight data architecture can store immutable raw files, processed features, analysis scripts and versioned models. This is not merely data management; it permits a later researcher to determine exactly which geometry and process history produced a given fatigue result.

A minimum digital record should distinguish commanded process parameters from measured process signals and final-part characteristics. For example, commanded exposure time is not the same as measured irradiance; nominal strut diameter is not as-built diameter; nominal implant preload is not necessarily retained preload after settling. Digital-twin credibility depends on updating the model with measured states rather than assuming perfect execution of the digital plan. Sensor data, metrology and inspection therefore form the observational layer of the twin.

Interoperable datasets should also contain failure information. Fractography images, crack-origin labels, pore descriptors, wear maps and coating-delamination measurements can become multimodal data for interpretable ML. The scientific opportunity is to train models that predict not only a scalar strength value but a failure mode or spatial damage field. This is more aligned with Mechanical Engineering because it preserves the link between data and mechanism.

For researchers with limited access to advanced sensors, the same principle can be implemented at modest scale: standardized specimen IDs, machine logs, 3D scan deviations, SEM images and mechanical curves stored in a structured directory and linked by a metadata table. The research value comes from traceability and consistency, not from the size of the database. This architecture can later support transfer learning, federated studies or collaborative benchmark datasets across dental and Mechanical Engineering laboratories.

Table 7. Research-gap-to-method roadmap for a mechanical-engineering research program

Priority gap	Strong method chain	Validated deliverable
AM zirconia defects	DOE -> 3D metrology/micro-CT -> fatigue -> fractography -> FEA	Process-defect-fatigue reliability map
Printed resin cure engineering	Orientation/post-cure -> FTIR/Raman/DMA -> ageing -> fatigue	Cure-dose-conversion-fatigue window
Accuracy-strength-productivity	3D deviation + mechanics + build time -> surrogate/Pareto search	Robust clinically constrained AM process window
Smart coating durability	Coating state -> adhesion -> wear/tribocorrosion -> residual fatigue	Durability-function Pareto map
Manufacturing-informed FEA	As-built geometry/properties -> nonlinear contact FEA -> DIC/strain	Quantified model-fidelity benefit and validation protocol
Patient-specific inverse design	Space-filling FEA -> surrogate -> MOO -> re-FEA/bench confirmation	Uncertainty-aware inverse-design workflow
Digital twin / interoperability	Traceable process + metrology + mechanics + time-state update	Time-resolved risk map with defined domain of validity
Sustainable intelligent manufacturing	Energy/material/cost + quality/life -> robust Pareto optimization	Performance-cost-environment decision map

Experimental, metrological and statistical discipline

A strong doctoral program should be built as an evidence chain rather than a collection of independent tests. If the hypothesis is that build orientation changes fatigue because it changes flaw orientation, the minimum chain is orientation -> defect/anisotropy measurement -> static screening -> fatigue -> fracture origin -> model validation. If the hypothesis is that a coating improves implant performance, the chain is deposition parameters -> thickness/roughness/adhesion -> wear/tribocorrosion or cyclic shear -> residual fatigue -> biological or functional endpoint. Each measurement should either quantify an input, a state variable or a validation response.

Standardized simple specimens and anatomically realistic components should be used at different stages. Bars/discs are useful for process screening because stress fields are interpretable; crowns, frameworks and implants are useful for final transferability. A common error is to begin immediately with complex anatomical parts, where material, geometry and contact effects are confounded. Conversely, a PhD that never progresses beyond bars may not demonstrate component relevance.

The statistical architecture should be planned at the same time as the mechanical experiment. Screening studies may use factorial or fractional-factorial designs to identify the dominant manufacturing variables, whereas optimization studies require response-surface or sequential designs that resolve curvature and interactions. Replication is needed to estimate process scatter; randomization should be used where practical to avoid confounding build order, furnace batch or testing sequence with the intended factors. For additive manufacturing, build position and build job should be recorded because specimens from one job are not always statistically independent. A mixed-effects formulation can distinguish fixed process factors from random batch/build effects when sufficient data are available.

Sample size should be justified by the expected effect and variability rather than copied from previous papers. Static mechanical tests may need fewer specimens than fatigue or Weibull reliability studies, because lifetime distributions are broader and run-outs contain information. Pilot data can estimate variance and inform power calculations, but the pilot settings should not be used repeatedly to tune the hypothesis and then treated as independent confirmation. For machine-learning studies, the effective sample size is the number of independent manufacturing conditions or components, not simply the number of rows created by repeated measurements. Splitting multiple observations from the same specimen across training and test sets creates data leakage and unrealistically high prediction accuracy.

Validation criteria should be defined before model fitting. For FEA, agreement can be expressed as error in strain, displacement, contact force, fracture load or failure location under one or more conditions not used in calibration. For a surrogate or ML model, report held-out error, calibration/uncertainty where applicable and performance on an unseen geometry, material batch or process setting. For optimization, confirmation experiments should include the predicted optimum plus at least one baseline/control, with the same measurement protocol. The relevant question is not

whether the optimizer returns a solution, but whether that solution produces a statistically and mechanically meaningful improvement when built and tested.

Finally, significance and engineering importance should be separated. A small change may be statistically significant yet irrelevant to fit tolerance or fatigue survival, while a clinically meaningful reduction in failure probability may not reach significance in an underpowered experiment. Reporting effect size, confidence intervals and physically defined acceptance thresholds allows the reader to distinguish these cases. This decision-oriented statistical framework is essential if a PhD aims to deliver a process window or design rule rather than a sequence of pairwise comparisons.

High-value research pathways

A doctoral problem becomes clear when five elements are specified: material, manufacturing/surface route, controllable variables, performance responses and method/validation. Figure 8 demonstrates this objective generator. The framework prevents titles such as 'Study of 3D-printed dental materials' because it forces the researcher to define what is controlled and what causal mechanism is being tested.

The strongest objectives typically use verbs that imply engineering knowledge: quantify, model, correlate, identify, predict, validate, optimize and establish a process/design window. 'Compare' can be one step but should not be the thesis endpoint. A publishable PhD should generate a relation or model that allows a result to be predicted outside the exact tested combination, followed by independent validation.

Quantify the effect of build orientation, layer thickness and sintering schedule on pore architecture, shrinkage anisotropy and fatigue reliability of additively manufactured zirconia.

Develop a cure-conversion-property model for definitive DLP/SLA crown resins linking post-curing energy and geometry to conversion gradients, water uptake, anisotropy and fatigue life.

Optimize printing orientation, layer thickness and support strategy simultaneously for marginal fit, flexural/fatigue performance and manufacturing time using a multi-objective DOE/ML framework.

Compare additive and subtractive routes through quantified defect populations rather than only mean strength, and develop a defect-informed reliability model for matched dental geometries.

Develop and validate a tribocorrosion-fatigue protocol for surface-engineered titanium implant materials that separates mechanical wear, electrochemical loss and synergistic damage.

Engineer a multifunctional implant coating and determine the trade-off among roughness, wettability, coating adhesion, cyclic shear/fatigue, corrosion resistance and antibacterial/bioactive function.

Develop manufacturing-informed FEA using measured anisotropic material properties, micro-CT defect maps and realistic contact; validate with DIC or strain-gauge measurements.

Create a patient-specific implant inverse-design framework using FEA-generated datasets, a calibrated surrogate model and constrained multi-objective optimization with independent re-FEA and experimental verification.

Develop a time-resolved digital-twin concept for implant healing that updates interfacial stiffness and loading risk using mechanobiological state variables and validated surrogate prediction.

Use in-situ or layer-image data from dental AM to detect defects and predict final dimensional/mechanical quality using interpretable machine learning.

Construct an open, traceable dental AM benchmark dataset containing machine metadata, process parameters, metrology, microstructure and mechanical responses to enable cross-laboratory ML validation.

Perform sustainability-aware optimization of dental manufacturing routes by including energy, waste, cycle time, cost and durability in a common Pareto framework.

Representative project blueprints

Blueprint A - Defect-informed AM zirconia: Hypothesis: the fatigue reliability of printed zirconia is controlled by orientation-dependent pore/flaw architecture created jointly by printing and sintering. Use a factorial orientation-layer-sintering design, 3D scan/micro-CT,

density/XRD/SEM, flexure/Weibull and step-stress fatigue. Register representative defects to FEA and validate predicted failure locations. Final output: a process-defect-fatigue design map. The evidence base includes Alghauli et al. [5], Pinelli et al. [19], Ruggiero et al. [6], Sabatini et al. [28] and Bergler et al. [29].

Blueprint B - Cure engineering of definitive printed resin: Hypothesis: post-cure energy and build orientation create conversion gradients that explain a substantial part of anisotropy and long-term fatigue scatter. Vary orientation, post-cure time/temperature/device and specimen thickness; map conversion with FTIR/Raman, hardness and DMA; perform water/thermocycling and fatigue; fit an orthotropic life model. Final output: cure dose-conversion-fatigue window. Rizzante et al. [3], Mudhaffer et al. [4], Korkmaz et al. [21], Flottes et al. [47] and Dascanio et al. [46] motivate the design.

Blueprint D - Smart implant coating durability: Hypothesis: a bioactive or antimicrobial coating fails functionally when cyclic contact and corrosion degrade adhesion, even if initial biological response is high. Vary coating thickness/deposition parameters; measure roughness, wettability, chemistry and adhesion; apply cyclic shear/wear plus electrochemistry; assess residual adhesion/fatigue and functional response. Final output: coating durability-function Pareto map. Aissi et al. [8], Abdo et al. [32], Balang et al. [10], Jadhav et al. [11] and Pytel' et al. [34] frame the need.

Blueprint E - Manufacturing-informed implant/crown FEA: Hypothesis: measured manufacturing anisotropy and surface/geometry deviations alter predicted stresses enough to change design conclusions. Characterize material directionality and scan actual components; compare idealized, measured-geometry and process-informed FE models; validate with DIC/strain under controlled load. Final output: quantified model-fidelity benefit and a validation protocol. Poovarodom et al. [35], Sahin Hazir et al. [36], Azhdari et al. [12] and Harikrishna et al. [37] motivate this progression.

Blueprint F - Neural-surrogate patient-specific implant inverse design: Hypothesis: validated surrogate models can search a patient-specific implant design space orders of magnitude faster than direct iterative FEA without losing decision accuracy. Generate a space-filling FEA design set including diameter, length, thread/angle, bone quality and load; train/validate a surrogate; perform NSGA-II/PSO/Bayesian optimization; re-run high-fidelity FEA and bench test selected designs. Final output: uncertainty-aware inverse-design workflow. Chen et al. [13] and Prados-Privado [14] demonstrate feasibility.

Blueprint G - Time-dependent digital twin for osseointegration mechanics: Hypothesis: load recommendations should evolve with interfacial stiffness rather than assuming immediate full osseointegration. Build a mechanobiological evolution model calibrated from literature/experimental data, couple it with FEA and a fast surrogate, and validate against staged mechanical/clinical proxy measurements where feasible. Final output: time-resolved risk map and decision rules. Rodriguez-Molinero and Prados-Privado [15] provides the direct contemporary starting point.

Blueprint H - Sustainable intelligent dental manufacturing: Hypothesis: the lowest-waste process is not necessarily the lowest-impact process when energy, post-processing, tool wear and service life are included. Meter energy/material use for AM and CAD/CAM routes; quantify accuracy and fatigue/wear; calculate normalized environmental/cost indicators; build a multi-objective model and validate selected designs. Final output: performance-cost-sustainability Pareto decision map, extending the gap identified by Pytel' et al. [34].

Four-year execution and publication logic

Year 1 should establish the research system. Complete the focused/systematic literature review, select one primary material/process platform, verify machine repeatability and measurement systems, perform pilot DOE, and define the causal state variables to be measured. A first paper can be a critical review or process-characterization study. The gate at the end of Year 1 is whether the chosen factors produce reproducible and mechanistically interpretable differences.

Year 2 should generate the core process-structure-performance dataset. Use a statistically justified DOE, measure microstructure/defects/conversion/surface state and perform service-relevant mechanical or tribological tests. The main publication should

demonstrate a causal relation rather than a ranking. Data should be curated in a machine-readable structure from the beginning so it can support later modelling.

Year 3 should develop and validate the computational or data-driven model. FEA inputs should be measured where possible; surrogate models should use independent test data; uncertainty and sensitivity should be reported. The publication target is a model that predicts an experimental response not used in calibration. For implant or restoration research, at least one anatomically representative component should be used for validation.

Year 4 should perform multi-objective optimization, confirmation experiments and translation. The model should identify a robust process/design window, Pareto set or patient-specific decision rule. Final experiments should include one predicted optimum and one deliberately non-optimal control to demonstrate discriminatory power. The thesis contribution can be expressed as a validated process map, inverse-design workflow, coating durability criterion, digital twin or sustainability-aware manufacturing guideline.

Recommended reporting framework

The current literature would become substantially more reusable if dental AM and surface-engineering papers adopted a minimum manufacturing metadata set. For photopolymerized resins this should include printer, technology, resin lot, orientation, layer, support, exposure information when available, wash solvent/time, post-cure device and time/temperature, storage before test and aging protocol. For ceramic AM, green-part orientation, solids loading where available, debinding and sintering schedules, shrinkage, density and surface finishing should be reported. For metal AM, machine, powder/alloy specification, layer, scan/energy parameters when possible, build direction, heat treatment, surface finishing and porosity should be included.

Mechanical tests should report specimen geometry, surface state, environment, loading rate/frequency, load ratio, failure definition and replicate count. Fatigue should report censored/run-out data and survival/statistical method. Surface studies should report 3D topography and coating thickness/adhesion in addition to biological endpoints. FEA should report mesh convergence, complete material/contact definitions, load and boundary conditions, sensitivity and validation. AI/ML studies should report dataset provenance, train/validation/test split, leakage controls, prediction uncertainty and performance on unseen geometry or material conditions.

This reporting discipline is not administrative overhead; it is the prerequisite for reproducibility, meta-analysis, transferable machine learning and eventual digital twins. Without standardized metadata, dental manufacturing remains a collection of isolated machine-material demonstrations rather than an engineering knowledge base.

CONCLUSIONS

This focused critical review of 50 peer-reviewed publications from 2025–2026 shows that advanced dental materials are best interpreted as manufactured states rather than nominal chemical classes. Across polymers, ceramics, metals and surface-engineered systems, orientation, layer thickness, exposure/post-cure, firing/sintering, machining, finishing and coating parameters modify defects, microstructure, conversion, residual stress, roughness and geometry; these state variables then govern accuracy, fatigue, wear, adhesion and durability. The revised study-selection and synthesis framework makes this causal logic explicit and provides a reproducible basis for comparing heterogeneous studies without implying a PRISMA-style exhaustive search.

The critical evidence gaps are equally clear. Additive-manufacturing studies require more defect-informed and aged fatigue evidence; coating and surface studies require durability testing that retains mechanical and functional endpoints in the same experiment; FEA requires greater use of measured process-specific properties, realistic interfaces, uncertainty analysis and independent validation; and AI/ML requires traceable datasets, leakage-resistant evaluation, unseen-domain testing and high-fidelity confirmation. These limitations explain why promising results do not automatically translate across machines, materials, geometries or patient conditions.

A closed-loop MSP digital thread is therefore proposed:

control manufacturing and surface variables; measure the produced structure, defects, interfaces and geometry; test service-relevant performance; calibrate and validate mechanistic FEA; curate traceable data; use interpretable surrogates to accelerate prediction; perform robust multi-objective optimization; and experimentally confirm the selected process/design window. This integration provides a coherent route from descriptive material comparison to predictive, validated and sustainability-aware dental manufacturing while preserving explicit limits on evidence quality and generalizability.

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