



Artificial intelligence integrated with CAD/CAM for automated design of dental restorations

Inteligencia artificial integrada con CAD/CAM para el diseño automatizado de restauraciones dentales

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ABSTRACT

Computer-aided design and manufacturing has transformed restorative dentistry, but the design step remains a manual and operator-dependent bottleneck. Artificial intelligence has been proposed to automate it. This narrative review synthesizes the integration of artificial intelligence with CAD/CAM for the automated design of dental restorations across five thematic axes: margin and preparation detection, automated restoration design, fit and quality assessment, manufacturing integration, and workflow and human-machine collaboration. The review draws on sources published up to 2025. The evidence shows that artificial intelligence can detect preparation margins, generate restoration designs, and assess fit, with accuracy approaching that of human technicians in the best studies, but the studies are small, heterogeneous, and mostly in vitro, and the transfer of the automated designs to clinically acceptable restorations is not yet established. The main limitation is the gap between the geometric accuracy that the models achieve and the clinical acceptability that the restorations require. The review concludes that artificial intelligence is a promising assistant to the CAD/CAM workflow rather than a replacement for the technician, and that the field should validate the automated designs clinically before unattended use can be recommended.

Keywords: artificial intelligence; computer-aided design; dental prosthesis; dental restoration; computer-aided manufacturing; deep learning.

RESUMEN

El diseño y la fabricación asistidos por computador han transformado la odontología restauradora, pero el paso de diseño sigue siendo un cuello de botella manual y dependiente del operador. Se ha propuesto la inteligencia artificial para automatizarlo. Esta revisión narrativa sintetiza la integración de la inteligencia artificial con CAD/CAM para el diseño automatizado de restauraciones dentales en cinco ejes temáticos: detección de márgenes y preparaciones, diseño automatizado de restauraciones, evaluación del ajuste y la calidad, integración con la fabricación, y colaboración hombre-máquina en el flujo de trabajo. La revisión se apoya en fuentes publicadas hasta 2025. La evidencia muestra que la inteligencia artificial puede detectar márgenes de preparación, generar diseños de restauraciones y evaluar el ajuste, con una precisión que en los mejores estudios se acerca a la de los técnicos humanos, pero los estudios son pequeños, heterogéneos y mayormente in vitro, y la transferencia de los diseños automatizados a restauraciones clínicamente aceptables no está establecida. La principal limitación es la brecha entre la precisión geométrica que logran los modelos y la aceptabilidad clínica que requieren las restauraciones. La revisión concluye que la inteligencia artificial es un asistente prometedor del flujo CAD/CAM, no un reemplazo del técnico, y que el campo debe validar clínicamente los diseños automatizados antes de recomendar su uso sin supervisión.

Palabras clave: inteligencia artificial; diseño asistido por computador; prótesis dental; restauración dental; fabricación asistida por computador; aprendizaje profundo.

INTRODUCTION

Computer-aided design and computer-aided manufacturing have transformed restorative dentistry over the past four decades, replacing much of the lost-wax casting that once defined the field with a digital workflow in which a restoration is designed on a screen and milled or printed from a block or a resin.^(1,2) The workflow has shortened the time from preparation to delivery and has made the restoration more consistent, but it has not removed the human from the loop: the design step, in which a technician positions the restoration and sculpts its anatomy, remains manual, time-consuming, and dependent on the skill of the operator.⁽³⁾ The technology that underpins this workflow has been described and reviewed repeatedly, and its maturation over the past decades is the background against which the current artificial intelligence work must be read.^(4,5) The persistence of the manual design step, even as the surrounding workflow became digital, is itself evidence of how much skill and judgement the step contains, and it is the reason the automation of this step is a harder problem than the automation of the scanning or the milling that flank it.⁽³⁾ The progression from the manual craft, through the digital workflow, to the automated design is the arc that this review traces, and the question it addresses is how far along that arc the field has actually come.

The design step is the natural next target for automation, because it is well defined, repeated on every case, and bounded by the anatomy of the prepared tooth and the opposing dentition. Artificial intelligence has been proposed to perform this step, and the integration of machine learning with the CAD/CAM workflow has attracted a growing number of studies since 2018.^(6,7) The appeal is the same as elsewhere in dental artificial intelligence: to make a slow, variable, and skilled human task faster, more consistent, and more widely available.⁽⁸⁾ The digital restoration workflow, from the intraoral scan to the finished prosthesis, is now sufficiently standardized that it offers a clear sequence of targets for automation, and the studies have proceeded stage by stage along that sequence.^(9,10) The progression is also a progression in ambition, from the easier stages, where the model reads a boundary, to the harder stages, where the model must produce an object, and the field's confidence has grown as it has moved along this sequence.

The task differs from the diagnostic tasks that dominate dental artificial intelligence. Designing a restoration is a generative and geometric task, not a classification task, and its success is measured by the fit and the morphology of the produced object rather than by a diagnostic accuracy.⁽¹¹⁾ The question for the field is therefore not whether a model can recognize a margin but whether it can design a restoration that a clinician would accept, and this question has been answered only partially.⁽¹²⁾ The distinction between the generative and the diagnostic task is not merely technical; it changes the nature of the error, because a diagnostic error is a wrong label that can be corrected, whereas a design error is a physical object whose correction requires the object to be remade, and the cost and the consequence of the two errors are correspondingly different.⁽¹¹⁾ The higher cost of error is the reason the field has been more measured in its claims than the diagnostic literature, and it is the reason the phrase decision support rather than replacement recurs in the design literature.⁽³⁾

The aim of this narrative review is to synthesize how artificial intelligence is integrated with CAD/CAM for the automated design of dental restorations, organized across five thematic axes, and to identify what the evidence supports and what remains open. The review is written for clinicians and technicians who must judge whether, and how, to incorporate these tools into their workflows.⁽⁵⁾ The five axes are not intended to be exhaustive, but they follow the sequence of the digital workflow and therefore capture the questions that arise most consistently as a case moves from the prepared tooth to the finished restoration. The review does not recommend specific systems, which would be premature, but instead identifies the stable questions that any system, present or future, must answer before it can be trusted in the mouth.

METHODS

The methodological approach adopted for this review was informed by the Scale for the Assessment of Narrative Review Articles (SANRA), without applying the procedures associated with a systematic review.⁽¹³⁾ Relevant publications were identified through searches of bibliographic databases using combinations of keywords related to artificial intelligence, machine learning, deep learning, CAD/CAM technologies, dental restorations, crowns, and prosthetic design. Research articles published between 2018 and 2025 formed the primary evidence base, whereas earlier publications were considered when necessary to establish the historical background and conceptual

foundations of the field. Studies were selected according to their relevance to the predefined areas of investigation, and the available evidence was examined through a thematic narrative synthesis. Particular attention was given to publications addressing the application of artificial intelligence within CAD/CAM-based restorative dentistry, distinguishing this specific research domain from the broader literature on dental artificial intelligence and computer-aided dental technologies. Foundational studies on CAD/CAM systems were also incorporated to contextualize technological developments and methodological advances. Consequently, the scope of the review reflects the intersection of these research areas as represented in the literature identified through the search strategy.

The analysis was structured around five thematic domains established prior to the synthesis: identification of preparation margins and tooth geometry, AI-assisted restoration design, evaluation of restoration fit and quality, integration with manufacturing processes, and optimization of clinical workflows through human–AI interaction. These domains were arranged to reflect the progression of digital restorative procedures, beginning with the acquisition and interpretation of prepared dental structures and extending through restoration development, fabrication, and clinical implementation. Each publication was classified according to its principal contribution to the corresponding stage of this process. An overview of the five domains and their most relevant findings is provided in Table 1.

Table 1. Thematic axes of artificial intelligence in CAD/CAM restoration design.

Axis	Role of artificial intelligence	State of the evidence
Margin and preparation detection	Detects the preparation margin	High accuracy on clean scans
Automated restoration design	Generates the restoration geometry	Preliminary and mostly in vitro
Fit and quality assessment	Measures fit and detects discrepancies	Approaching human reliability
Manufacturing integration	Adapts the design to the machine	Emerging
Workflow and collaboration	Divides routine from judgement	Accepted as a starting point

DEVELOPMENT

Margin and preparation detection

The first step of the automated workflow is the detection of the preparation margin and the prepared tooth, because the restoration is defined against this boundary and any error here propagates into the entire design.(14,15) The margin is the most difficult part of the preparation to detect reliably, because it is in many cases obscured by blood, gingiva, or the scan, and the models that detect it are the foundation on which the later stages rest.(15) The preparation margin is also the part of the workflow where the clinical and the technical requirements meet, because the clinician prepares the tooth and the model must then read the preparation, and the mismatch between what the clinician intended and what the model reads is a source of error that the automated workflow must absorb.(14)The margin detection is the stage at which the field most directly inherits the long literature on preparation design, because the detectability of a margin is partly determined by how the clinician prepared the tooth, and a model cannot detect a margin that the preparation does not make visible.(15)

The evidence shows that deep learning can detect the preparation margin and the prepared tooth with high accuracy on intraoral scans, and that the detected margin is the input to the automated design that follows.(16,17) The accuracy of the margin detection is reported in terms of the distance between the detected and the reference margin, and the best studies report errors small enough that the subsequent restoration is not compromised.(14)The margin detection is nonetheless sensitive to the quality of the scan and to the presence of soft tissue, and the studies that report the highest accuracy use clean, well-isolated preparations.(17)The influence of the preparation design and of the scanning conditions on the margin detection is a recurring concern, and the studies that examine it find that the detection degrades on irregular or subgingival margins.(18)The margin is therefore not a fixed difficulty but a variable one, and a model that performs well on the clean preparations of a study may perform less well on the messy preparations of a clinic, which is the same caveat that attaches to the diagnostic applications of the same technology. The morphological studies that report the detected margin alongside the reference show where the

error concentrates, and they provide the per-landmark view that a summary distance conceals. (16,17)

The significance of this axis is that it converts the automated workflow from a sequence of separate models into a pipeline, in which the output of the margin detection feeds the design and the design feeds the manufacturing. The integration of the stages is as important as the accuracy of any single stage, and the studies that report a complete pipeline are more informative than those that report a single stage in isolation.(19) The benchmark datasets that have begun to appear, which provide a common set of preparations and a common measure of margin detection, are the infrastructure that a comparison of methods requires, and their absence until recently is one reason the field has been hard to compare.(19)The pipeline view also reveals where the errors accumulate, because an error at the margin detection is inherited by the design and then by the manufacturing, and a pipeline that is accurate at each stage can still compound small errors into a clinically visible one at the end.(19)

Automated restoration design

The second axis is the automated design of the restoration itself, which is the core of the field's ambition. The task is to generate, from the prepared tooth and the surrounding anatomy, a restoration with the correct shape, contact, and occlusion, and the approaches range from generative models that produce the entire restoration to methods that adapt a template or a library tooth to the specific case.(20-22)The design is the stage at which the field's ambition is most directly tested, because it is here that the model must produce, not merely recognize, and the difference between producing and recognizing is the difference between the design task and the diagnostic tasks that precede it in the literature.(20)

The evidence on the quality of the automatically designed restorations is positive but preliminary. Studies report that the generated restorations are geometrically close to those designed by a human technician, and that the automatic designs are produced in a fraction of the time, but the comparison is in most studies made in vitro and on a limited range of cases.(21,22) The preliminary nature of the evidence is a consequence of the task's difficulty rather than of a lack of interest, and the field has grown rapidly enough that the studies now span several approaches and several restoration types, which is the breadth on which a more definitive synthesis will eventually rest. The evidence is therefore best read as a demonstration that the task is tractable, and the question that remains is whether the tractable task can be performed to the clinical standard that the restoration requires, and whether the performance holds outside the controlled conditions of the laboratory and in the mouth of the individual patient under the conditions of actual, everyday, real-world, routine clinical use. The morphology of the automatic design, its cusps and its contacts, is the part that the models find hardest, because it is the part that is most variable across patients and most subject to clinical judgement.(23)The accuracy of the automatic designs, when compared with the technician's design, is reported as high in several studies, and the automatic systems are described as producing a clinically acceptable starting design that the technician then refines.(24,25) The machine learning approaches to the design range from generative adversarial networks to template adaptation, and the studies that compare them report broadly similar geometric accuracy with different strengths in morphology and in speed.(26-28)The time saved by the automatic design is the clearest and most consistent benefit, and it is reported across the studies regardless of the approach, which suggests that the immediate value of the technology is in efficiency rather than in a step change in the quality of the restoration.(21,22) The restoration types addressed range from single crowns to more complex restorations, and the complexity of the case is a further variable that the studies have only begun to explore, with the single-unit cases better covered than the multi-unit ones.(20,29) The clinical question that follows, whether the automatic design leads to a restoration that functions and survives as well as a manual one, is the question that the in vitro studies cannot answer and that the field has yet to address directly.(12)

The approaches to the design reflect different views of what a restoration should be. A template-based approach reproduces a library tooth and adapts it, which is fast and predictable but can produce a restoration that looks generic, whereas a generative approach learns the distribution of natural anatomy and can produce a more individual restoration but with less control.(11,21) The field has not settled on which approach is better, and the answer may depend on the type of restoration and on the clinical situation.(29)The comparison of the approaches on the same cases is the study that the field most needs, because the current studies each report a single approach on its own cases, and the resulting numbers are not directly comparable.(29)The choice between the approaches is not only technical but also philosophical, because it reflects a view of whether a

restoration is a standard object to be reproduced or an individual object to be created, and the two views have different implications for how much the technician's judgement remains in the loop.(11)

Fit and quality assessment

The third axis is the assessment of the fit and the quality of the restoration, which is both a use of artificial intelligence in its own right and a necessary check on the automated design. The marginal fit, the internal fit, and the occlusion of the restoration are the measures by which it is clinically judged, and the models can be used to measure these as well as to produce the restoration.(14,30)

The evidence shows that artificial intelligence can measure the marginal fit and can detect the discrepancies that would make a restoration unacceptable, with a reliability that approaches that of a human examiner.(31,32) The measurement of fit is a natural application of the same image analysis that underlies the diagnosis, and it benefits from the fact that a fit discrepancy is a geometric fact rather than a matter of judgement.(31)The evaluation of the restoration is also the point at which the automated workflow can be assessed as a whole, and the studies that evaluate the full pipeline report a marginal fit within the clinically acceptable range in the cases they examine.(33,34) The fit assessment is the bridge between the geometric and the clinical, because it is the fit, more than any other single property, that determines whether a restoration succeeds or fails in the mouth, and the measurement of it is therefore the most clinically meaningful of the measures that the field reports.(32)

The quality assessment closes the loop of the automated workflow, because it allows the system to flag a restoration that its own design stage produced inadequately. A pipeline in which the design is generated, milled, and then checked by the same system is only as trustworthy as the checking stage, and the independence of the assessment from the design is a point that the studies have not always addressed.(32,35) The assessment stage is also where the field connects to the long-established literature on marginal fit, which predates the artificial intelligence work and provides the thresholds of clinical acceptability against which the automatic restorations should be judged, and the comparison with that literature is a benchmark the studies should adopt.(30) The adoption of that benchmark would ground the field's claims in a standard that clinicians already accept, and it would convert the reported accuracies from abstract numbers into statements about whether the restoration would be judged acceptable by the criteria that the profession already uses.(30)

Manufacturing integration

The fourth axis is the integration of the automated design with the manufacturing step, the milling or the printing that produces the physical restoration. The integration is the point at which the digital design becomes a clinical object, and the accuracy of the manufacturing determines whether the good design becomes a good restoration.(36,37) The manufacturing step is where the digital promise meets the physical constraint, and a design that is geometrically perfect but unmanufacturable, or manufacturable only with a loss of accuracy, is a failure of integration rather than of design.(37)The comparison of the manufacturing technologies, milling against printing, is a subject of its own, and the accuracy that each achieves is a property of the machine and the material that the artificial intelligence layer must respect rather than override.(37)

The evidence on this axis is partly a question of the manufacturing technology rather than of the artificial intelligence, because the accuracy of milling and printing is a property of the machine and the material as much as of the design.(37)The contribution of the artificial intelligence is to ensure that the design that is sent to the machine is one that the machine can produce, and that the design is adjusted for the specific machine and material, which is a level of integration that the studies have begun to address.(36,38) The distinction between the accuracy of the design and the accuracy of the manufacturing is important, because a good design can be degraded by a poor machine and a poor design cannot be rescued by a good one, and the studies that report the two separately are the ones that allow the reader to see where the error enters.(36)The digital workflow is only as strong as its weakest stage, and the integration of the artificial intelligence with the manufacturing is therefore a question of where the error enters the chain as much as of how accurate each stage is in isolation.(37) The practical consequence is that the accuracy of the automated design cannot be judged in isolation from the manufacturing that follows it, and a complete evaluation must carry the restoration through the entire chain to the physical object and, ultimately, to the patient.

The integration also includes the finishing steps, the sintering, the glazing, and the fit veri-

fication, which are the parts of the workflow where the digital chain meets the manual one. The artificial intelligence does not remove these steps, but it can inform them, by predicting where a restoration is likely to fail or where the fit is likely to be marginal, and the studies that report this predictive use are the most clinically oriented of the field.(39,40) The choice of material and its interaction with the design is a further consideration, because the design that is optimal for one material is not optimal for another, and the models that account for the material are a step beyond those that design in the abstract.(41)The biomechanical behavior of the restoration, its strength and its stress distribution, is the link between the geometry and the clinical outcome, and the studies that connect the design to the biomechanics are the ones that move the field toward a clinically meaningful measure of quality.(42)The manufacturing axis is therefore where the field broadens from a geometric to an engineering problem, and where the question of whether the restoration will survive in service begins to be answered.(42)

Workflow and human-machine collaboration

The fifth axis is the place of the human in the automated workflow, which is the question that the earlier axes raise but do not answer. The automated workflow does not remove the technician but changes the technician's task, from designing the restoration to supervising and correcting the design, and the collaboration between the human and the machine is the axis on which the adoption of the technology ultimately depends.(3,43) The question of the human's place is not a residual question but the decisive one, because the technology will be adopted to the extent that it fits the human's workflow and respects the human's judgement, and rejected to the extent that it does not.(3)The history of CAD/CAM itself shows this: the technology was adopted not when it could produce a restoration, but when it could produce one that the technician could trust and correct, and the artificial intelligence layer faces the same threshold.(5)The technology that respects the technician, and that is designed around the correction rather than the replacement, is the technology that will be adopted, and the field's own acceptance studies already point in this direction.(43)

The evidence on this axis is mostly about acceptance and efficiency. Studies report that the automated workflow reduces the design time, and that clinicians and technicians find the automatic design acceptable as a starting point that they then adjust, but that they do not trust it as a final product.(3,43) The acceptance is the practical measure of the field's maturity, and it is lower than the geometric accuracy would suggest, because a restoration is a clinical object with consequences that a technician does not delegate lightly.(3)The gap between the measured accuracy and the expressed trust is itself a finding, and it suggests that the barriers to adoption are not primarily technical but are about confidence, accountability, and the value that the technician attaches to their own judgement.(3)The gap between the measured accuracy and the expressed trust is itself a finding, and it suggests that the barriers to adoption are not primarily technical but are about confidence, accountability, and the value that the technician attaches to their own judgement.(3)The acceptance studies are a reminder that a technology is adopted by people, not by metrics, and that the people who must adopt this one are the technicians whose skill the technology is meant to extend, not to replace, which is a relationship that the field would do well to respect in its design and its framing.(43)

The division of labor that emerges is a division by difficulty. The model produces the routine parts of the design, the bulk of the restoration and the initial anatomy, and the technician attends to the parts that require judgement, the occlusion, the contacts, and the aesthetic refinement, which are the parts that the model finds hardest.(44,45) This division is the most likely near-term form of the collaboration, and it is the form that the literature supports.(43)The division also has an economic meaning, because the time saved on the routine parts is the time that the technician can then spend on the parts that require their skill, and the value of the technology is realized precisely in this reallocation rather than in the elimination of the technician.(3)The economic argument is the one most likely to drive adoption in practice, where the technician's time is the scarce resource, and the studies that report the time savings are therefore the ones that speak most directly to the practitioner.(3)

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DISCUSSION

Across the five axes, a consistent picture emerges. Artificial intelligence can perform the stages of the CAD/CAM design workflow, from margin detection to design generation to fit assessment, with geometric accuracy that approaches the human technician in the best studies, but the studies are small, heterogeneous, and mostly in vitro, and the clinical acceptability of the automatically designed restorations is not yet established.(8,11) The gap between the geometric accuracy and the clinical acceptance is the central finding of the review.(12)The trajectory mirrors the earlier history of CAD/CAM itself, which was adopted first as a laboratory tool and only later, after validation, as a clinical one, and the artificial intelligence layer is likely to follow the same path.(1,5)

The gap has a specific explanation. The geometric accuracy of the models is measured against a reference, a margin, a library tooth, or a technician's design, and the models are good at reproducing that reference, but the clinical acceptability of a restoration depends on factors that the reference does not capture, the occlusion, the contacts, and the aesthetics, which are matters of judgement rather than of geometry.(23)The models are therefore being measured against the part of the task that they do well, and their weakness on the part that they do less well is not yet measured at all.(22)The consequence is that the reported accuracy is a lower bound on the clinical difficulty, and a reader who takes the geometric accuracy as a measure of clinical readiness will overestimate the technology.(43,45) The occlusion and the contacts are the clearest examples: they are the features that most affect the function and the longevity of the restoration, and they are the features that the geometric measures, which compare the design against a reference surface, capture least well.(23,35) The occlusion is also the feature that most requires the opposing arch and the mandibular movement, which are not always present in the datasets on which the models are trained, and the absence of the dynamic information is a structural limit that the geometric studies do not report but that the clinical studies will reveal.(23)

The comparison with the diagnostic applications of dental artificial intelligence is instructive. In diagnosis, the model's output is a classification that a clinician can accept or reject, and the stakes of an error are contained; in restoration design, the model's output is a physical object that will be placed in a patient, and the stakes of an error are realized in the mouth.(11)The higher stakes explain the lower trust and the slower adoption, and they justify the caution with which the literature itself treats its own results.(12)The difference in stakes also explains why the design task, despite being technically well suited to automation, has not been automated as quickly as the diagnostic tasks, and why the field has been more willing to present its results as assistance rather than as replacement.(3)The same pattern has played out in the manufacturing side of the field, where the automation of milling and printing was adopted gradually and with validation, and the design automation is likely to follow the same measured path.(37)

The limitations of this review are those of a young and heterogeneous literature. The studies are mostly in vitro, single-center, and limited in the range of restoration types and clinical situations, and the review therefore cannot assess the clinical performance of the automated workflows, because that evidence does not yet exist.(45)The selection was narrative rather than systematic, and the rapid pace of publication means that the account is a snapshot. The review also cannot compare the models head to head, because the studies use different datasets and different measures, and the field lacks a shared benchmark.(19)These limitations are themselves informative, because they describe a field at the point where the technical feasibility has been shown and the clinical validation has not, and where any synthesis is necessarily a progress report rather than a verdict.(12)The reader should therefore treat the geometric accuracies reported here as evidence of feasibility, not as evidence of clinical readiness, and should await the clinical studies that will settle the latter. The review's own method, a narrative selection of a rapidly moving literature, is also a limitation, and a systematic update once the clinical evidence accrues would be a natural next step.

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The agenda that follows is concrete. For research, the field needs clinical studies that place the automatically designed restorations in patients and measure their fit and their survival, not merely their geometric agreement with a reference.(12)For the technology, the field needs to measure the parts of the design that the models find hard, the occlusion, the contacts, and the aesthetics,

rather than only the parts they find easy. For the workflow, the field needs to define the division of labor between the model and the technician, and to build the interface that supports that division. (3)The agenda is therefore not a call for more models but for better evaluation of the models that exist, and for the translation of the geometric results into the clinical measures that will determine whether the technology is adopted.(12)The field has reached the point where its technical capability exceeds its clinical evidence, and the next step is not to make the models more accurate but to make them more trusted, which is a matter of validation rather than of engineering.

The agenda also has an evaluative component. The field needs a shared benchmark and a shared measure, so that the studies can be compared and the progress can be tracked, and it needs the threshold of clinical acceptability, drawn from the marginal fit literature, to be applied to the automatic designs so that their success is measured against the same standard as the manual designs.(19,30) Without these, the field will continue to report accuracy against its own references, and the reader will be unable to judge whether the technology is ready for the clinic or merely ready for another study.(12)

CONCLUSIONS

Artificial intelligence can perform the stages of the CAD/CAM restoration design workflow, from margin detection to design generation to fit assessment, with geometric accuracy that approaches the human technician in the best studies, but the evidence is small, in vitro, and does not yet establish the clinical acceptability of the automatically designed restorations. The models reproduce the geometric reference well and the clinical judgement less well, and the occlusion, the contacts, and the aesthetics remain the parts that require the technician. The most likely near-term role of the technology is therefore as an assistant that performs the routine parts of the design and leaves the judgement to the human, rather than as a replacement for the technician. The field should validate the automated workflows clinically, and it should measure the parts of the design that matter clinically, before unattended use can be recommended. The trajectory of the field, from a manual craft to a digital workflow to an automated one, is the same trajectory that the earlier CAD/CAM transition followed, and the lesson of that transition is that the technology is adopted when it is validated, not when it is demonstrated, which is the stage the field has now reached.

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