Artificial Intelligence-Supported Digital Implant Planning: A Literature-Based Framework for Assessing Accuracy and Workflow Efficiency

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Abstract

Conventional digital implant planning is vulnerable to operator-dependent variability and time burden, particularly during segmentation and multimodal registration. Artificial intelligence (AI) has therefore been introduced to automate and assist these upstream steps with the goal of improving reproducibility and workflow efficiency. This review compares conventional and AI-supported planning across segmentation performance, implant positioning accuracy, workflow efficiency and clinical decision-making. Current evidence indicates that AI-supported workflows can improve the consistency of anatomical models, reduce planning time and support more reproducible decision-making. However, improvements in planned-to-placed implant accuracy appear more modest and constrained by imaging quality, manufacturing tolerances and intra-operative factors. Overall, AI-supported planning is best understood as a decision-support adjunct rather than a replacement for clinician judgement. The available literature supports its value in improving workflow consistency and efficiency, while highlighting the need for cautious clinical interpretation due to heterogeneous outcome reporting and limited prospective evidence.

Introduction

Digital implant planning enables prosthetically driven, pre-surgical decision-making by integrating cone beam computed tomography (CBCT) with complementary surface datasets (e.g., intraoral scans) to create a virtual patient for implant positioning and guide fabrication (Hämmerle et al., 2015; Shujaat et al., 2021). CBCT provides volumetric assessment of ridge morphology and proximity to anatomic features (e.g., the mandibular canal, maxillary sinus) or local pathologies, supporting implant planning with appropriate safety margins (Bornstein et al., 2014). Within this workflow, multimodal registration and anatomical segmentation are critical stages in determining the anatomical boundaries and risk structures used to define trajectory, clearance and safety margins (Shujaat et al., 2021).

Conventional digital planning typically relies on manual or semi-manual segmentation with clinician-led registration. These steps are time-intensive and susceptible to inter- and intra-operator variability, particularly in low-contrast or artefact-affected regions, which can reduce reproducibility and extend planning time (Mureșanu et al., 2022; Codari et al., 2017; Wanderley et al., 2021). As such, AI-supported workflows aim to standardise these upstream processes by using deep-learning segmentation and automated or assisted registration. This potentially improves reproducibility and reduces workload (Elgarba et al., 2024; Macrì et al., 2024; Ntovas et al., 2024a).

This review synthesises and critically compares conventional and AI-supported digital implant planning across key domains that influence clinical translation: segmentation performance, implant positioning accuracy, workflow efficiency and clinical decision-making. The focus is on how AI may influence the reliability and efficiency of the planning workflow, while recognising that clinical implementation remains dependent on appropriate case selection, image quality, clinician oversight and validation of the final plan.

Review Approach

This article presents a narrative literature review of conventional and AI-supported digital implant planning. Relevant literature was considered across CBCT segmentation, multimodal registration, implant positioning accuracy, workflow efficiency, clinical decision-making and implementation challenges. Priority was given to systematic reviews, validation studies and recent studies reporting clinically relevant outcomes such as segmentation agreement, registration accuracy, planning time, inter-observer variability and planned-to-placed implant deviation. The review is not intended to be a systematic review or meta-analysis; rather, it provides a structured synthesis of the current evidence and its clinical implications.

Digital Implant Planning Workflow

Following multimodal registration, anatomical segmentation is a key interpretive step because it defines the boundaries and risk structures used to set trajectory and safety margins (Shujaat et al., 2021; Hämmerle et al., 2015). Conventional workflows typically involve manual segmentation (thresholding with slice-by-slice refinement), introducing operator dependence and measurable inter-observer variability, particularly under low-contrast or artefact-affected conditions (Mureșanu et al., 2022; Codari et al., 2017; Wanderley et al., 2021).

AI-supported workflows have been introduced at this segmentation and integration stage to standardise upstream inputs through automated/semi-automated segmentation and AI-assisted registration (Elgarba et al., 2024; Macrì et al., 2024; Zheng et al., 2025). Validation studies report strong geometric agreement for deep-learning CBCT segmentation across relevant structures, supporting improved reproducibility of the anatomical models used for planning (Lahoud et al., 2021; Preda et al., 2022; Jindanil et al., 2023). More recent systems may also provide implant-position suggestions and risk visualisation within the same environment, shifting clinician effort towards verification and refinement rather than manual model construction (Macrì et al., 2024; Elgarba et al., 2024; Mureșanu et al., 2022).

Taken together, these developments define two comparable workflows: clinician-driven manual planning versus AI-assisted decision support. Despite the clear workflow advantages of AI in the available evidence, these benefits should be interpreted as improvements to the planning workflow rather than definitive evidence of superior surgical outcomes. Table 1 summarises the workflow-stage contrasts and their implications for reproducibility, efficiency, and clinical translation.

Table 1. Synthesis of Conventional vs AI-Supported Digital Implant Planning Workflows

Workflow Stage	Conventional Digital Planning	AI-Supported Digital Planning	Key Evidence & Implications
CBCT Segmentation	Manual; operator-dependent; sensitive to artefacts/low-contrast regions	Automated/semi-automated deep-learning segmentation (teeth, bone, sinus, canal); high reproducibility	AI generally improves geometric accuracy and reduces inter-observer variability, strengthening the anatomical basis for planning
Anatomical Variability & Reproducibility	High inter-/intra-observer variation (notably mandibular canal, thin cortical plates)	Standardised outputs reduce inter-/intra-observer variation	Benefits are greatest in complex anatomy or artefact-affected regions
Implant Positioning Accuracy	Trajectory chosen manually based on interpreted anatomy	Trajectory guided by more consistent models and automated cues	Accuracy gains are usually modest and mainly reflect upstream stabilisation rather than direct optimisation
Multimodal Registration	Manual CBCT-IOS alignment; cumulative	AI-assisted/automated registration; fewer	More consistent registration supports prosthetically

	registration error risk	adjustment cycles	driven planning
Workflow Efficiency	Time-intensive segmentation and revisions; high cognitive load	Reduced planning time; clinician focus shifts to verification	Efficiency gains are among the most consistent advantages, even when positional accuracy gains are small
Clinical Decision-Making & Safety	Risk assessment subjective; variable canal clearance/safety margins	Standardised risk visualisation; improved inter-planner agreement	Best framed as decision-support rather than an autonomous planner
Clinical Translation	Predictability relies on individual expertise	Greater consistency and scalability, especially in complex cases	Clinical benefit strongest as decision-support adjunct rather than autonomous system
Limitations	Operator dependency; time burden	Domain shift, data bias, limited long-term clinical validation	Evidence for workflow benefit is stronger than evidence for improved surgical outcomes

Comparative Analysis: AI vs Conventional Digital Workflows

This section critically compares conventional and AI-supported digital implant planning across key stages of the pre-surgical workflow. The analysis focuses on diagnostic imaging and segmentation, implant positioning accuracy, workflow efficiency, and clinical decision-making, as these domains have the greatest influence on planning reliability and clinical translation. Differences between workflows are evaluated in terms of reproducibility, efficiency, and downstream implications rather than technical performance alone.

Diagnostic Imaging and Segmentation

In conventional digital workflows, segmentation relies on manual thresholding and slice-by-slice contour refinement, which is both skill-dependent and labour-intensive (Mureșanu et al., 2022; Shujaat et al., 2021). Systematic reviews describe high inter- and intra-observer variability when delineating the mandibular canal, sinus floor, and thin cortical plates (Mureșanu et al., 2022; Shujaat et al., 2021), particularly under low-contrast conditions or in the presence of CBCT artefacts such as beam hardening and blooming (Codari et al., 2017; Wanderley et al., 2021). Under these conditions, boundary error widens and reproducibility declines.

By contrast, AI-based segmentation demonstrates consistently narrower error distributions and reduced operator dependence. Across multiple validation studies, deep-learning models, predominantly convolutional neural networks (CNNs) derived from U-Net architectures, achieve high geometric agreement for teeth and maxillofacial structures (Lahoud et al., 2021; Preda et al., 2022; Al-Asali et al., 2024). Comparative evaluations further show improved continuity and reproducibility of mandibular canal segmentation compared with manual tracing, even in low-contrast datasets (Jindanil et al., 2023; Al-Asali et al., 2024). In effect, AI stabilises the anatomical model used for planning, reducing inter-operator divergence at downstream decision points.

At the same time, these gains remain bounded by CBCT voxel resolution, partial-volume effects, and artefact severity, which impose upper limits on achievable precision irrespective of segmentation method (Bornstein et al., 2014; Codari et al., 2017; Wanderley et al., 2021). Generalisability may be limited by domain shift (Mureșanu et al., 2022; Macrì et al., 2024). AI therefore improves segmentation consistency rather than eliminating error, a distinction that directly affects downstream implant positioning performance.

Implant Positioning Accuracy

Implant positioning accuracy reflects the cumulative effect of upstream segmentation fidelity and multimodal registration (Shujaat et al., 2021; Saini et al., 2024). It is typically reported as 3D coronal (entry) deviation, apical deviation, and angular deviation between planned and placed implants (Saini et al., 2024). Entry deviation reflects displacement at the implant platform, apical deviation reflects displacement at the implant apex, and angular deviation reflects the difference in implant trajectory; together, these measures describe both positional and directional accuracy of surgical transfer (Tahmaseb et al., 2018; Saini et al., 2024).

In conventional digital planning, trajectories are selected manually from segmented CBCT datasets. This labour-intensive step is significantly influenced by clinician experience and introduces inter-planner variability, particularly when segmentation is uncertain or registration requires repeated adjustment (Shujaat et al., 2021; Saini et al., 2024). As a result, variability can arise even before surgical transfer, through differences in the interpretation of boundaries and safety margins when defining a trajectory.

AI-supported planning predominantly improves positioning by stabilising upstream inputs rather than changing the surgical transfer process (Elgarba et al., 2024; Macrì et al., 2024). More consistent segmentations reduce variation in perceived boundary locations, narrowing the range of acceptable trajectories chosen across planners (Elgarba et al., 2024; Macrì et al., 2024). Additionally, AI-based CBCT-IOS superimposition may improve alignment consistency compared with manual registration, reducing cumulative geometric drift in the virtual plan (Ntovas et al., 2024b; Zheng et al., 2025). Collectively, these effects primarily increase the consistency of the virtual plan rather than substantially altering the physical accuracy limits of surgical placement.

Despite these advantages, improvements in placement accuracy are usually modest (sub-millimetre reductions in entry/apex deviation and small angular changes) (Saini et al., 2024). This is expected because accuracy is bounded by CBCT voxel resolution and artefact effects, as well as guide manufacturing tolerances and intra-operative handling, which limit how much upstream gains can translate into surgical deviation reductions (Bornstein et al., 2014; Wanderley et al., 2021; Saini et al., 2024; Hämmerle et al., 2015). The net effect is a narrower error distribution and improved reproducibility, rather than a major shift in absolute accuracy ceilings.

This distinction is clinically important because AI may improve the reliability of the virtual plan without necessarily overcoming the physical sources of surgical transfer error, including guide seating, sleeve tolerance, drill length, bone density and operator handling (Hämmerle et al., 2015; Tahmaseb et al., 2018; Saini et al., 2024). Therefore, improved AI segmentation or registration should be interpreted as strengthening the planning foundation rather than guaranteeing improved planned-to-placed accuracy.

Workflow Efficiency

Workflow efficiency represents one of the most consistent advantages of AI integration. Conventional digital planning requires time-intensive manual segmentation, iterative boundary refinement, and repeated adjustment during multimodal registration, imposing substantial cognitive and temporal burden on clinicians (Bessadet et al., 2024; Shujaat et al., 2021; Ntovas et al., 2024a). This time burden is important because it can shape adoption, standardisation, and the feasibility of applying high-quality planning at scale.

AI-based segmentation substantially reduces the time required to generate anatomical models by automating labour-intensive contouring tasks (Ntovas et al., 2024a; Macrì et al., 2024). Validation studies demonstrate that deep-learning segmentation of the mandibular canals and the registration of the model obtained from the intraoral scan with the CBCT can be completed within minutes, shifting the clinician's role from manual construction to verification and targeted correction (Ntovas et al., 2024a; Jindanil et al., 2023; Zheng et al., 2025). AI-assisted registration further reduces adjustment cycles and improves alignment stability compared with manual methods (Ntovas et al., 2024b; Zheng et al., 2025). Consequently, AI tends to reallocate clinician effort from repetitive technical steps towards oversight, plausibility checking, and risk-focused refinement.

Efficiency gains should be interpreted independently from accuracy outcomes. Reduced planning time does not inherently imply improved implant positioning accuracy, which remains constrained by imaging and surgical transfer variables (Saini et al., 2024; Macrì et al., 2024). The principal contribution of AI lies in standardisation and scalability rather than overcoming imaging or surgical transfer limitations (Elgarba et al., 2024; Macrì et al., 2024).

Clinical Decision-Making and Safety

Clinical decision-making in implant planning involves balancing prosthetic objectives with biological safety (Hämmerle et al., 2015; Shujaat et al., 2021). In conventional workflows, subjective interpretation of manually segmented anatomy contributes to variability in risk assessment and trajectory selection, especially in borderline cases (Shujaat et al., 2021; Saini et al., 2024). This creates a safety-relevant dependency on individual expertise, especially when structures at risk are difficult to visualise or margins are tight.

Given the improved reproducibility of segmentation and registration described above, AI-supported workflows can reduce ambiguity in canal clearance and bone availability assessment and support more consistent risk appraisal during planning (Elgarba et al., 2024; Macrì et al., 2024). Studies evaluating AI-assisted planning report higher inter-planner agreement, quantified using intraclass correlation coefficients, compared with manual workflows (Elgarba et al., 2024; Macrì et al., 2024). These gains may support safer and more consistent planning, while clinical responsibility and medicolegal accountability remain centred on the supervising clinician (Uribe, 2025).

Patient and Economic Outcomes

Direct evidence linking AI-supported implant planning to improved patient-centred outcomes remains limited, with most data inferred from digital workflow studies more broadly (Saini et al., 2024). Improved planning consistency may reduce intra-operative adjustments and support smoother surgical workflows, which could enhance patient experience (Saini et al., 2024; Bessadet et al., 2024). Retrospective evidence suggests that high-quality planning is associated with fewer prosthetic complications, although this does not yet demonstrate that AI-specific gains translate into measurable long-term outcome improvements (Da Silva et al., 2014).

From an economic perspective, systematic reviews suggest that upfront investment in digital workflows can be offset by reduced planning time, revision cycles, and chairside adjustments (Bessadet et al., 2024). AI may further amplify these efficiencies, but AI-specific cost-effectiveness evidence remains sparse (Elgarba et al., 2024; Macrì et al., 2024). Overall, the evidence supports AI's value in improving planning consistency and efficiency more strongly than its ability to improve near-term clinical or long-term patient outcomes (Saini et al., 2024; Elgarba et al., 2024; Macrì et al., 2024).

Limitations, Challenges and Ethical Considerations

Despite demonstrable advantages in segmentation consistency and workflow efficiency, AI-assisted digital implant planning faces several technical, clinical, economic, and ethical constraints that currently limit its translation into routine practice (Elgarba et al., 2024; Macrì et al., 2024).

A central technical limitation relates to generalisability. As synthesised in the previous section, most deep-learning models for CBCT segmentation and planning are trained on institution-specific datasets with limited variation in scanner type, voxel size, artefact burden, and patient anatomy. This creates a well-recognised domain-shift problem, whereby performance observed during internal validation does not reliably transfer to external datasets or alternative acquisition protocols (Mureșanu et al., 2022; Macrì et al., 2024; Minnema et al., 2021). The absence of standardised, cross-scanner benchmarking datasets further restricts meaningful comparison between algorithms and hampers clinical confidence in model robustness (Mureșanu et al., 2022; Macrì et al., 2024). Additionally, downstream reductions in implant deviation remain modest even when segmentation metrics improve, so improved technical performance should not be assumed to translate into clinically meaningful accuracy gains (Saini et al., 2024; Macrì et al., 2024).

From a clinical perspective, AI-supported planning introduces risks associated with automation bias. Deep-learning systems often operate as "black boxes", limiting transparency regarding error sources and failure modes. This increases the risk that clinicians may over-trust algorithmic outputs, particularly in complex cases, unless robust verification practices are maintained (Ahmed et al., 2021). These concerns extend into the medicolegal domain, where responsibility for adverse outcomes becomes less clearly defined when treatment decisions arise from a combination of clinician judgement and algorithmic recommendation (Uribe, 2025). Current regulatory frameworks provide limited guidance on liability allocation in such hybrid decision-making models, reinforcing the necessity of explicit human oversight. Accordingly, positioning AI as decision support (rather than autonomous planning) aligns with the regulatory expectation that safety is maintained through meaningful human oversight and clinician-led decision-making.

From an implementation standpoint, this requires routine clinician verification of segmentation, registration and final implant positioning, alongside documentation of corrections and clear communication of model limitations to mitigate automation bias (Ahmed et al., 2021; Uribe, 2025).

Ethical and data-governance requirements further constrain AI implementation because model development and validation often rely on large CBCT datasets that may constitute personal data. Under the GDPR/UK GDPR principles, processing must be lawful, fair and transparent and limited to what is necessary for the stated purpose (data minimisation) (Legislation.gov.uk, 2016). Identifiability risk must be managed where datasets are reused or shared: effectively anonymised data fall outside data-protection law, whereas pseudonymised data remain personal data and therefore remain within scope (ICO, 2025). In UK health research settings, transparency about secondary uses of data is generally expected, and whether REC review is required should be determined before repurposing clinical imaging for algorithm training (Health Research Authority, 2018). In addition, bias amplification remains a significant ethical risk: if training datasets under-represent particular anatomical presentations or demographic groups, AI systems may systematically underperform in those populations, possibly exacerbating inequities (Mureșanu et al., 2022; Elgarba et al., 2024).

Finally, a consistent limitation across the literature is the lack of high-quality prospective or randomised clinical trials directly linking AI-enhanced planning to improved surgical accuracy or long-term patient outcomes. Most published studies remain retrospective, simulated, or single-centre, limiting causal inference and clinical generalisation (Elgarba et al., 2024; Macrì et al., 2024). Addressing this evidence gap is essential before AI-assisted implant planning can be considered a validated clinical standard.

Before clinical implementation, AI tools should therefore be locally validated against the imaging protocols, scanner settings and patient populations in which they will be used. This is particularly important where models have been trained on external datasets or where software performance may vary across CBCT machines, voxel sizes and artefact profiles.

Altogether, these constraints demonstrate that technological performance alone is insufficient to justify uncritical clinical adoption. Current evidence supports AI-assisted implant planning as a workflow-enhancing adjunct that can improve efficiency and planning reproducibility, but its effect on surgical accuracy and long-term patient outcomes remains less certain. Clinical use should therefore remain clinician-led, with AI outputs verified against patient-specific anatomy, imaging quality and prosthetic requirements.

Discussion

This review synthesises evidence comparing AI-supported and conventional digital implant planning across segmentation performance, implant positioning accuracy, workflow efficiency and clinical decision-making. Across the literature, the most consistent benefits of AI are observed in upstream stages of the workflow, particularly in segmentation and registration, where variability in anatomical interpretation drives downstream planning accuracy and reproducibility.

Validation studies and systematic reviews report better AI segmentation performance than manual approaches on overlap- and distance-based metrics, with the greatest benefit in low-contrast, artefact-affected and anatomically complex regions. These improvements reduce inter- and intra-operator variability and produce more stable 3D anatomical models, supporting more consistent safety-margin assessment near critical structures. AI also consistently improves workflow efficiency.

Conversely, improvements in implant positioning accuracy are typically modest. The most defensible contribution of AI is therefore improved reproducibility and a narrower error distribution rather than a step-change in absolute accuracy limits. This suggests that the main clinical value of AI lies in standardising the quality of planning inputs, while final interpretation, risk assessment and treatment planning remain clinician-led.

Although findings are directionally consistent, the overall quality of evidence supporting AI benefits is mixed. Much of the literature comprises retrospective, simulated or single-centre evaluations with heterogeneous endpoints and limited external validation, which increases risk of bias and restricts causal inference. Consequently, current evidence is best interpreted as promising for reproducibility and efficiency outcomes but insufficient to claim definitive clinical superiority on surgical positional accuracy.

Prospective controlled comparisons using consistent deviation metrics remain scarce, so the current literature does not yet justify claiming that AI-supported planning is clinically superior to conventional digital planning in reducing surgical positional error. The strongest current conclusion is that AI improves the reproducibility and efficiency of the planning process, while surgical outcomes remain dependent on imaging quality, guide fabrication, operator execution and clinician oversight.

Conclusion

Current evidence indicates that AI primarily augments digital implant planning by improving the consistency of CBCT segmentation and multimodal registration, while also increasing workflow efficiency. These benefits can reduce inter-operator variability, shorten planning time, and support more consistent clinician decision-making. However, improvements in implant positioning accuracy are generally modest and remain constrained by imaging quality, manufacturing tolerances, and intra-operative factors. Overall, AI-supported digital implant planning is best understood as a clinician-led decision-support adjunct rather than a replacement for professional judgement or a proven method for improving surgical outcomes. The available literature supports its role in enhancing planning consistency and efficiency, while highlighting the need for cautious interpretation due to heterogeneous evidence and limited prospective clinical validation.

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