

Factors Affecting Expenditure Evaluation in Dentofacial Surgical Correction: A Specialist-Oriented Investigation

Dr. Emily Johnson, DDS, MS

Dr. Department of
Orthodontics and
Dentofacial Orthopedics
Harvard School of Dental
Medicine
Boston, Massachusetts,
United States

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ABSTRACT

Dentofacial surgical correction, particularly orthognathic surgery, represents a highly specialized and resource-intensive domain of maxillofacial intervention. Expenditure evaluation in this field is not merely a financial exercise but a multidimensional assessment involving clinical complexity, imaging technology, surgical planning systems, and specialist decision-making variability. This study develops a structured analytical perspective on the factors influencing expenditure evaluation in dentofacial surgical correction from a specialist-oriented standpoint, integrating clinical, computational, and decision-theoretic dimensions.

The research synthesizes insights from surgical simulation frameworks, three-dimensional imaging methodologies, and advanced computational modeling approaches to understand cost formation mechanisms. Foundational contributions such as computer-aided surgical simulation (CASS) systems highlight how digital planning improves procedural accuracy while simultaneously increasing preoperative costs due to computational and technical resource requirements (Xia, 2005; Xia, 2015). Similarly, 3D reconstruction and surface modeling techniques such as marching cubes and quadric error metrics demonstrate the technological complexity embedded in modern surgical workflows (Lorensen and Cline, 1987; Garland and Heckbert, 1997).

From a computational perspective, advances in graph-based learning and point cloud processing systems, including PointNet, PointNet++, and graph convolutional networks, illustrate the increasing role of algorithmic modeling in surgical planning and anatomical interpretation (Qi et al., 2017; Kipf and Welling, 2017). These tools indirectly influence expenditure evaluation by redefining diagnostic precision and specialist workload distribution.

Importantly, specialist-oriented variability remains a critical determinant of cost estimation. Prior clinical-economic investigations emphasize that differing specialist preferences significantly influence procedural planning and cost structures in orthognathic interventions (Lone et al., 2023). This variability introduces subjectivity into expenditure evaluation models, making standardization challenging.

The study concludes that expenditure evaluation in dentofacial surgical correction is shaped by a convergence of technological intensity, computational integration, and specialist-dependent decision frameworks. The findings suggest the need for hybrid evaluation models that incorporate both algorithmic cost prediction systems and clinician-driven judgmental parameters.

Keywords: Dentofacial surgery; orthognathic surgery; expenditure evaluation; surgical simulation; point cloud processing; graph neural networks; specialist variability; healthcare cost modeling.

1. Introduction

Dentofacial surgical correction, particularly orthognathic surgery, occupies a critical position in craniofacial healthcare due to its dual functional and aesthetic objectives. The complexity of such procedures arises not only from anatomical variability but also from the integration of advanced imaging technologies, surgical

planning systems, and interdisciplinary clinical decision-making. Consequently, expenditure evaluation in this domain extends beyond conventional cost accounting and becomes a multidimensional analytical challenge involving clinical, technological, and specialist-driven determinants.

Historically, orthognathic surgical planning relied heavily on two-dimensional radiographic interpretation and surgeon experience. However, the emergence of computer-aided

surgical simulation (CASS) systems has significantly transformed preoperative planning. These systems enable three-dimensional visualization, predictive modeling of surgical outcomes, and enhanced precision in surgical execution (Xia, Gateno, & Teichgraber, 2005). Subsequent advancements have refined these approaches further, enabling full procedural simulation and sequencing in complex double-jaw surgeries (Xia, 2015). While these systems improve clinical outcomes, they simultaneously introduce new cost layers associated with software, computational infrastructure, and specialist training.

The increasing adoption of digital modeling techniques, including surface reconstruction algorithms such as marching cubes and quadric error metrics, has further expanded the computational demands of dentofacial surgery planning (Lorensen and Cline, 1987; Garland and Heckbert, 1997). These methodologies allow highly detailed anatomical reconstructions, but their implementation requires significant processing resources and technical expertise, which directly influence expenditure evaluation frameworks.

Recent advancements in machine learning and geometric deep learning have introduced additional complexity into surgical planning ecosystems. Neural architectures such as PointNet, PointNet++, and KPConv have enabled direct processing of 3D point cloud data, enhancing diagnostic precision and anatomical segmentation (Qi et al., 2017; Thomas et al., 2019). Graph neural networks (GNNs) and spectral filtering approaches further extend these capabilities by enabling relational modeling of anatomical structures (Kipf and Welling, 2017; Wu et al., 2021). While these technologies improve decision accuracy, they also increase dependency on computational infrastructure, thereby influencing cost evaluation metrics.

Despite these technological advancements, expenditure evaluation in dentofacial surgical correction is not purely algorithmic. It is significantly influenced by specialist judgment, institutional practices, and variability in clinical interpretation. Prior studies have shown that differences in specialist perspectives can lead to significant variation in cost estimation and procedural planning, particularly in orthognathic surgery contexts (Lone et al., 2023). This introduces a critical human factor that interacts with computational systems, making expenditure evaluation a hybrid socio-technical process.

Furthermore, broader healthcare economic frameworks suggest that procedural cost evaluation must account for preoperative planning, intraoperative execution, and postoperative management. In dentofacial surgery, each of these phases is influenced by both technological intensity and clinician decision-making. For instance, advanced imaging increases preoperative costs but may reduce intraoperative uncertainty, thereby potentially lowering overall expenditure variability.

The relevance of this study lies in its attempt to integrate these multidimensional influences into a coherent analytical framework. By examining technological, computational, and specialist-driven determinants collectively, the research aims to provide a structured understanding of expenditure evaluation mechanisms in dentofacial surgical correction.

2. Literature Review

The literature on dentofacial surgical correction and its associated expenditure evaluation spans clinical surgery, biomedical engineering, computational geometry, and healthcare economics. A synthesis of these domains reveals a complex interplay between technological innovation and specialist-dependent variability.

Early foundational work in orthognathic surgical planning emphasized manual cephalometric analysis and surgeon expertise as primary determinants of procedural outcomes. However, the introduction of computer-aided surgical simulation systems marked a paradigm shift. Xia et al. (2005) demonstrated that CASS systems significantly improve accuracy in complex craniofacial deformity correction by enabling three-dimensional preoperative simulation. This innovation reduced intraoperative uncertainty but increased preoperative resource utilization. Later, Xia (2015) extended this framework by proposing algorithmic sequencing for double-jaw surgeries, highlighting the increasing computational dependency of surgical planning workflows.

From a computational geometry perspective, Lorensen and Cline (1987) introduced the marching cubes algorithm, which remains foundational in 3D surface reconstruction. Similarly, Garland and Heckbert (1997) proposed quadric error metrics for surface simplification, enabling efficient representation of anatomical structures. These methods significantly reduced computational overhead while maintaining geometric fidelity, thereby influencing cost efficiency in medical modeling pipelines.

Machine learning advancements have further transformed anatomical modeling. Qi et al. (2017) introduced PointNet, enabling direct processing of unordered point sets, which is particularly relevant for medical imaging data such as CT and CBCT scans. PointNet++ further improved hierarchical feature extraction, enhancing spatial understanding of complex anatomical regions. These architectures have been extended in subsequent works such as KPConv (Thomas et al., 2019), which introduced deformable convolution mechanisms for irregular point cloud data.

Graph-based learning approaches, including graph convolutional networks (Kipf and Welling, 2017), have expanded the analytical capabilities of medical imaging systems by modeling relational dependencies between anatomical structures. A broader synthesis of graph neural networks highlights their applicability in learning structured representations of biomedical data (Wu et al., 2021). These

computational advancements collectively contribute to improved diagnostic precision but also increase system complexity and operational costs.

Deep geometry learning approaches further extend these methodologies by integrating representation learning techniques for 3D anatomical data (Xiao et al., 2020). Such approaches enable more robust segmentation and classification of craniofacial structures, directly influencing surgical planning efficiency.

However, despite technological sophistication, human factors remain central to expenditure evaluation. Clinical-economic variability has been observed in multiple studies focusing on orthognathic surgery. Lone et al. (2023) emphasize that specialist preferences significantly influence cost-of-goods estimation in orthognathic procedures, demonstrating that even standardized surgical frameworks yield variable expenditure outcomes depending on practitioner judgment. This highlights a persistent gap between computational precision and clinical subjectivity.

Similarly, Souitaris et al. (2007) and Linan and Chen (2009) demonstrate that decision-making frameworks in professional environments are influenced by behavioral and perceptual factors. While these studies originate from entrepreneurship research, their theoretical implications extend to medical decision-making, particularly in understanding intention-driven variability among specialists.

Lima et al. (2014) further emphasize that institutional and systemic constraints shape professional decision-making outcomes, suggesting that expenditure evaluation cannot be fully standardized without accounting for contextual variability. Sieger et al. (2014) also highlight that structural and environmental factors significantly influence professional behavior, reinforcing the notion that cost evaluation is embedded within broader socio-organizational systems.

A key research gap emerges from this synthesis: while computational models have significantly advanced the precision of surgical planning, there is limited integration between algorithmic cost prediction systems and specialist-driven variability models. Existing literature either focuses on technological optimization or clinical-economic variability independently, but rarely integrates both dimensions into a unified expenditure evaluation framework.

This study positions itself within this gap by proposing a specialist-oriented analytical perspective that integrates computational modeling advancements with clinical decision variability. In doing so, it builds upon prior work in surgical simulation (Xia et al., 2005; Xia, 2015), geometric modeling (Lorensen and Cline, 1987; Garland

and Heckbert, 1997), and deep learning architectures (Qi et al., 2017; Kipf and Welling, 2017), while grounding its clinical-economic interpretation in specialist variability findings (Lone et al., 2023).

3. Methodology

3.1 Research Design and Conceptual Orientation

This study adopts a mixed conceptual-analytical research design combining systematic literature synthesis, computational framework mapping, and specialist-oriented expenditure modeling. The objective is not empirical data collection but the development of a structured explanatory model that integrates technological, clinical, and behavioral determinants of expenditure evaluation in dentofacial surgical correction.

The theoretical foundation is grounded in three intersecting domains:

1. Computational surgical modeling systems (e.g., CASS, 3D reconstruction)
2. Deep geometric learning frameworks (e.g., point clouds, graph neural networks)
3. Specialist decision variability in orthognathic surgery economics

This triadic structure enables interpretation of expenditure as a multi-layered system outcome, rather than a linear cost aggregation process.

The methodological orientation is further influenced by prior specialist-oriented economic modeling approaches in orthognathic surgery, where procedural cost variability is linked to practitioner preference structures and clinical judgment differences (Lone et al., 2023). This provides the conceptual anchor for integrating human decision variability into computational cost evaluation systems.

3.2 Data Source and Literature Corpus Construction

The study relies exclusively on the provided reference corpus (31 sources), which spans:

- Orthognathic surgical simulation systems (Xia et al., 2005; Xia, 2015)
- 3D reconstruction and surface modeling algorithms (Lorensen and Cline, 1987; Garland and Heckbert, 1997)
- Point cloud learning architectures (Qi et al., 2017; Thomas et al., 2019)
- Graph neural network methodologies (Kipf and Welling, 2017; Wu et al., 2021)

Healthcare decision variability and entrepreneurship-based behavioral models (Linan and Chen, 2009; Souitaris et al., 2007)

Specialist cost evaluation studies in orthognathic surgery (Lone et al., 2023)

A thematic coding framework was applied to categorize literature into four domains:

1. Surgical planning technologies
2. Computational geometry and AI-based modeling
3. Economic evaluation and cost structuring
4. Specialist behavioral variability

Each reference was coded according to its contribution to:

- Cost generation
- Cost reduction
- Decision variability
- System optimization

3.3 Analytical Framework Development

The study constructs a Hybrid Expenditure Evaluation Framework (HEEF) consisting of three interconnected layers:

3.3.1 Technological Cost Layer

This layer includes all expenditure influenced by computational systems:

- Imaging systems (CT, CBCT)
- 3D reconstruction algorithms
- Simulation software (CASS systems)
- Deep learning models for segmentation and classification

Key theoretical anchors:

- Marching Cubes algorithm for surface reconstruction (Lorensen and Cline, 1987)
- Quadric error metrics for optimization (Garland and Heckbert, 1997)
- PointNet and PointNet++ architectures for geometric learning (Qi et al., 2017)

This layer assumes that higher computational accuracy

increases preoperative cost but reduces intraoperative uncertainty.

3.3.2 Algorithmic Intelligence Layer

This layer captures AI-driven decision-support systems influencing surgical planning efficiency:

- Graph Convolutional Networks (Kipf and Welling, 2017)
- KPConv and deformable convolution models (Thomas et al., 2019)
- Graph-based relational modeling (Wu et al., 2021)

These systems introduce:

- Reduced manual segmentation cost
- Enhanced diagnostic precision
- Increased computational infrastructure dependency

The model assumes a non-linear cost relationship, where initial adoption increases expenditure but long-term efficiency reduces marginal cost per procedure.

3.3.3 Specialist Decision Variability Layer

This is the most critical and least deterministic layer, based on clinical-economic evidence.

According to specialist-oriented orthognathic cost analysis, practitioner preferences significantly influence:

- Choice of surgical protocol
- Imaging requirements
- Simulation depth
- Resource utilization intensity (Lone et al., 2023)

This layer introduces:

- Behavioral variability
- Institutional dependency
- Non-standardized cost structures

It is modeled as a stochastic variable influencing total expenditure.

3.4 Conceptual Mathematical Representation

Total expenditure (E) is modeled as:

$$E = T + A + S + \epsilon$$

Where:

- T = Technological cost component
- A = Algorithmic intelligence cost component
- S = Specialist variability factor
- ε = Systemic and institutional noise

Each component is further decomposed:

Technological Cost (T)

$T = f(\text{Imaging, Reconstruction, Simulation})$
 $T = f(\text{Imaging, Reconstruction, Simulation})$

Algorithmic Cost (A)

$A = g(\text{GNN, PointCloudModels, OptimizationComplexity})$
 $A = g(\text{GNN, PointCloudModels, OptimizationComplexity})$

Specialist Factor (S)

$S = h(\text{ClinicalPreference, ExperienceLevel, InstitutionalPolicy})$
 $S = h(\text{ClinicalPreference, ExperienceLevel, InstitutionalPolicy})$

This structure reflects that expenditure evaluation is not deterministic but semi-stochastic and layered.

3.5 Evaluation Procedure

The evaluation was conducted in five analytical steps:

Step 1: Reference Stratification

All references were classified into technological, computational, and behavioral domains.

Step 2: Cost Attribution Mapping

Each domain was mapped to expenditure drivers in dentofacial surgical workflows.

Step 3: Interaction Modeling

Interdependencies between AI systems and clinical decision-making were modeled.

Step 4: Variability Index Construction

A conceptual variability index (VI) was constructed:

$$VI = ST + AVI = \frac{S}{T + A} VI = T + AS$$

Higher VI indicates greater specialist influence over cost variability.

Step 5: Synthesis of Expenditure Evaluation Model

The final framework integrates deterministic computational costs with stochastic clinical variability.

4.6 Methodological Limitations

- Absence of empirical patient-level financial datasets
- Reliance on secondary literature synthesis
- Limited quantification of behavioral variability
- Potential over-generalization of computational cost models

Despite these limitations, the framework provides a theoretically grounded and integrative model for expenditure evaluation.

4. Results

The analysis reveals that expenditure evaluation in dentofacial surgical correction is fundamentally a multi-layered and non-linear system shaped by technological intensity, algorithmic adoption, and specialist-dependent variability.

First, the technological cost layer is identified as the most structurally stable component of expenditure. Imaging systems, 3D reconstruction algorithms, and simulation platforms such as CASS significantly contribute to baseline procedural costs (Xia et al., 2005). However, these systems also reduce intraoperative uncertainty, suggesting a trade-off between upfront expenditure and downstream surgical efficiency. Surface reconstruction methods such as marching cubes and quadric error metrics further enhance anatomical precision but increase computational resource utilization (Lorensen and Cline, 1987; Garland and Heckbert, 1997).

Second, the algorithmic intelligence layer demonstrates a non-linear cost trajectory. Deep learning models such as PointNet and PointNet++ improve segmentation accuracy in craniofacial imaging, reducing manual intervention requirements (Qi et al., 2017). However, advanced architectures such as graph convolutional networks introduce additional computational overhead, particularly in training and deployment phases (Kipf and Welling, 2017). This creates a paradoxical effect where algorithmic sophistication initially increases expenditure before stabilizing at scale.

Third, the specialist variability layer emerges as the most significant contributor to cost dispersion. Clinical decision-making differences, particularly in surgical planning depth and imaging preferences, create measurable variability in

expenditure outcomes. Prior evidence indicates that specialist preferences directly influence cost-of-goods structures in orthognathic procedures (Lone et al., 2023). This variability persists even when standardized computational tools are employed, indicating that human judgment remains a dominant cost determinant.

The interaction between these layers reveals a coupled dependency structure. High technological and algorithmic investment reduces procedural uncertainty but does not eliminate cost variability due to specialist discretion. Instead, it shifts variability from intraoperative unpredictability to preoperative decision intensification.

A key finding is the emergence of a cost stabilization threshold, where incremental technological improvements yield diminishing returns in expenditure reduction. Beyond this threshold, specialist variability becomes the dominant factor influencing total cost differences across cases.

Additionally, the study identifies that AI-based systems indirectly increase expenditure transparency by standardizing diagnostic outputs, yet fail to standardize clinical decision pathways. This leads to a hybrid cost environment where computational precision coexists with behavioral unpredictability.

Overall, expenditure evaluation in dentofacial surgical correction is best understood as a tri-layered dynamic system, where technological determinism is moderated by algorithmic complexity and ultimately constrained by specialist-dependent variability.

5. Discussion

The findings of this study highlight a fundamental tension between computational precision and clinical subjectivity in dentofacial surgical expenditure evaluation. While advanced imaging, simulation, and deep learning systems significantly enhance diagnostic accuracy, they do not eliminate variability in cost structures. Instead, they restructure the nature of variability.

The dominance of the technological cost layer aligns with prior surgical simulation research demonstrating that systems such as CASS improve precision but require substantial infrastructural investment (Xia et al., 2005; Xia, 2015). This confirms that digital transformation in orthognathic surgery is cost-intensive at the adoption stage. However, once integrated, these systems improve workflow efficiency, partially offsetting initial costs.

Algorithmic systems introduce a more complex dynamic. Graph neural networks and point cloud architectures improve anatomical representation and segmentation accuracy (Qi et al., 2017; Wu et al., 2021). However, their computational requirements create a dual-cost structure:

high training costs and moderate operational savings. This reinforces the notion that AI adoption in surgical contexts is economically front-loaded rather than uniformly cost-saving.

The most critical insight arises from the specialist variability layer. Consistent with prior findings in orthognathic surgical economics, practitioner preferences significantly influence procedural cost outcomes (Lone et al., 2023). This suggests that even in highly digitized environments, human judgment remains a primary determinant of expenditure variability. This finding challenges the assumption that technological advancement alone can standardize healthcare costs.

Comparatively, behavioral decision-making frameworks from non-medical domains further support this interpretation. Studies on entrepreneurial intention and decision variability suggest that professional choices are shaped by perceptual and contextual factors rather than purely rational optimization (Linan and Chen, 2009; Souitaris et al., 2007). In surgical contexts, this translates into variability in imaging usage, planning depth, and procedural conservatism.

A key contradiction identified is the coexistence of standardization and variability. While AI systems standardize data interpretation, they do not standardize clinical decision thresholds. This leads to a fragmented cost structure where technological uniformity coexists with behavioral heterogeneity.

The primary limitation of this model is its conceptual nature, lacking empirical validation through patient-level cost datasets. Additionally, the interaction effects between algorithmic systems and specialist behavior require further quantitative modeling.

Despite these limitations, the study provides a structured framework for understanding expenditure evaluation as a hybrid system. It suggests that future optimization efforts should focus not only on technological advancement but also on aligning specialist decision protocols with computational decision-support systems.

6. Conclusion

This study examined expenditure evaluation in dentofacial surgical correction through a specialist-oriented, multi-layered analytical framework integrating computational, technological, and behavioral determinants. The central finding is that expenditure in orthognathic and dentofacial surgical systems is not a linear aggregation of costs but a structured interaction of three interdependent layers: technological infrastructure, algorithmic intelligence systems, and specialist decision variability.

Technological systems such as computer-aided surgical simulation (CASS), three-dimensional reconstruction pipelines, and surface modeling algorithms significantly

define the baseline cost structure of surgical planning. These systems enhance anatomical precision and procedural predictability, but they simultaneously introduce high initial investment costs and infrastructure dependencies (Xia et al., 2005; Lorensen and Cline, 1987).

Algorithmic intelligence systems, including point cloud learning architectures and graph neural networks, further reshape expenditure evaluation by introducing non-linear cost dynamics. While these systems reduce manual intervention and improve diagnostic accuracy, they also require high computational resources and specialized implementation frameworks (Qi et al., 2017; Kipf and Welling, 2017). This results in a transitional cost effect where early-stage expenditure increases before long-term efficiency gains are realized.

However, the most influential determinant of expenditure variability remains specialist decision-making behavior. Evidence suggests that practitioner preferences significantly influence imaging depth, surgical planning complexity, and procedural execution pathways, thereby generating substantial variability in cost outcomes (Lone et al., 2023). This human factor persists even in highly digitized clinical environments, indicating that technological standardization alone is insufficient to normalize expenditure structures.

The study contributes to existing literature by proposing a Hybrid Expenditure Evaluation Framework (HEEF) that integrates deterministic computational costs with stochastic specialist variability. This framework highlights the necessity of combining AI-driven decision-support systems with standardized clinical protocols to reduce cost dispersion.

Future research should focus on empirical validation of the proposed framework using patient-level expenditure datasets, as well as the development of adaptive AI systems capable of learning specialist decision patterns to reduce variability. Additionally, interdisciplinary research combining clinical surgery, health economics, and machine learning is essential for advancing cost optimization strategies in dentofacial surgical correction.

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