

# Redefining Surgical Health Economics: The Potential of TabPFN for Real-Time Precision Modelling

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## Abstract

Health economic evaluations within surgical disciplines face considerable methodological hurdles, particularly in relation to cost-effectiveness analyses (CEA) and budget-impact modelling (BIM). Conventional predictive modelling frameworks generally necessitate extensive hyperparameter optimisation and pre-processing pipelines, yet these frameworks remain poorly aligned with the limited sample sizes characteristic of surgical investigations. Tabular Prior-data Fitted Networks (TabPFN) introduce a transformer-based foundation model calibrated for tabular datasets, demonstrating state-of-the-art predictive accuracy through in-context learning and obviating the requirement for task-dedicated training epochs. This narrative review articulates TabPFN's capacity to reshape surgical health economics by mitigating prevailing modelling constraints and by opening novel pathways for precision health economic outcomes research (P-HEOR). We first evaluate TabPFN's methodological strengths, thereafter delineating persistent gaps in extant economic frameworks. We further delineate focused use cases, such as dynamically responsive resource distribution, patient-tailored cost-effectiveness evaluations, and iterative budget-impact simulations. While practical barriers, including regulatory impediments and heterogeneous data ecosystem integration, persist, TabPFN's robust uncertainty quantification and superior performance in sparse datasets position it as a catalyst for methodological advancements in surgical economic evaluation. Subsequent investigations must emphasise the prototyping of surgery-tailored modules, the formulation of validation criteria, and the creation of sustainable operational pipelines to exploit TabPFN's pedagogical strengths.

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## Keywords

Tabular Prior-Data Fitted Networks, Health Economics, Data Science, Surgery, Cost-Effectiveness Analysis, Artificial Intelligence

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## 1. Introduction

Surgical procedures constitute one of the most capital- and labour-intensive facets of contemporary healthcare, with annual global totals surpassing 300 million interventions [1]. Rising procedural complexity, reflected in rapid technological advances, refined surgical techniques, and a broader spectrum of patient comorbidities, challenges the applicability of standard health economic evaluation frameworks. Conventional decision-analytic models typically assume homogeneous patient pathways and fixed resource utilisation, omissions that can skew cost-effectiveness conclusions in the surgical context. The launch of TabPFN, the first transformer-based foundation model specifically designed for tabular datasets, presents a promising methodological advance that can mitigate these shortcomings [2]. Distinct from traditional algorithms that demand extensive feature engineering and hyperparameter tuning, TabPFN leverages in-context learning to achieve generalisable inference, thereby accommodating the sparse or highly varied datasets that frequently characterise surgical health economics.

Current economic evaluations in surgical domains continue to depend heavily on traditional statistical approaches and first-generation machine learning algorithms. Such methods frequently falter when confronted with the fragmented, multidimensional, and context-sensitive characteristics of surgical datasets [3]. These limitations are compounded by the dual imperatives of generating clinically interpretable predictions and accommodating the heterogeneity of patient cohorts, surgical techniques, and institutional protocols. TabPFN, with its recently developed architecture, is designed to address these challenges in a cohesive manner; it offers robust performance even on limited sample sizes, accommodates heterogeneous variable types, naturally handles missing data, and captures intricate feature interactions without the need for extensive engineering. We therefore argue that TabPFN could catalyse a substantive reorientation in the economics of surgical care. Its contributions are likely to transcend modest improvements in accuracy, paving the way for modelling frameworks that were previously stymied by data scarcity and prohibitive computational demands.

## 2. Methodology

This paper adopts a narrative review approach to assess the potential of TabPFN in surgical health economics. Rather than undertaking a formal systematic mapping of health economic domains, we focus on synthesising theoretical insights, technical features, and existing literature to construct a forward-looking analytical framework. To ensure transparency of evidence synthesis, the literature search

encompassed databases including PubMed, Scopus, and Web of Science, covering publications from January 2010 to February 2025. Search terms combined “surgery”, “health economics”, “machine learning”, and “TabPFN” with Boolean operators. Inclusion criteria prioritised peer-reviewed English-language studies that reported quantitative or methodological findings relevant to surgical economic evaluations or tabular AI models. Grey literature and non-peer-reviewed pre-prints were excluded unless they contained seminal methodological innovations.

## **2.1. Literature Review and Gap Identification**

We conducted a focused literature review on three core areas: (1) existing methodological limitations in surgical health economic evaluations, (2) the architectural and performance characteristics of TabPFN, and (3) the application of foundation models in healthcare settings [4] [5]. This review provided a conceptual basis for evaluating TabPFN’s suitability for addressing persistent challenges in surgical economics.

## **2.2. Comparative Evaluation Framework**

We developed a thematic comparative framework to examine TabPFN in relation to traditional analytical methods, focusing on five key dimensions: computational efficiency, small-dataset performance, handling missing data, uncertainty quantification, and clinical interpretability. This framework enables a structured, qualitative assessment of TabPFN’s advantages and potential limitations.

## **2.3. Application Landscape Overview**

Rather than formally mapping surgical economic domains, we identify and categorise high-potential application areas through theoretical synthesis. These include precision health economic outcomes research (P-HEOR), dynamic budget impact modelling, and real-time resource allocation optimisation. For each, we articulate TabPFN’s theoretical advantages, current gaps in standard approaches, and illustrative examples.

## **2.4. Implementation Feasibility Considerations**

Drawing from existing literature on healthcare AI deployment, we explore the feasibility of implementing TabPFN across multiple domains [6]. Key factors considered include regulatory approval processes, data infrastructure requirements, organisational readiness, and cost-benefit trade-offs in real-world settings.

# **3. Current Challenges in Surgical Health Economics**

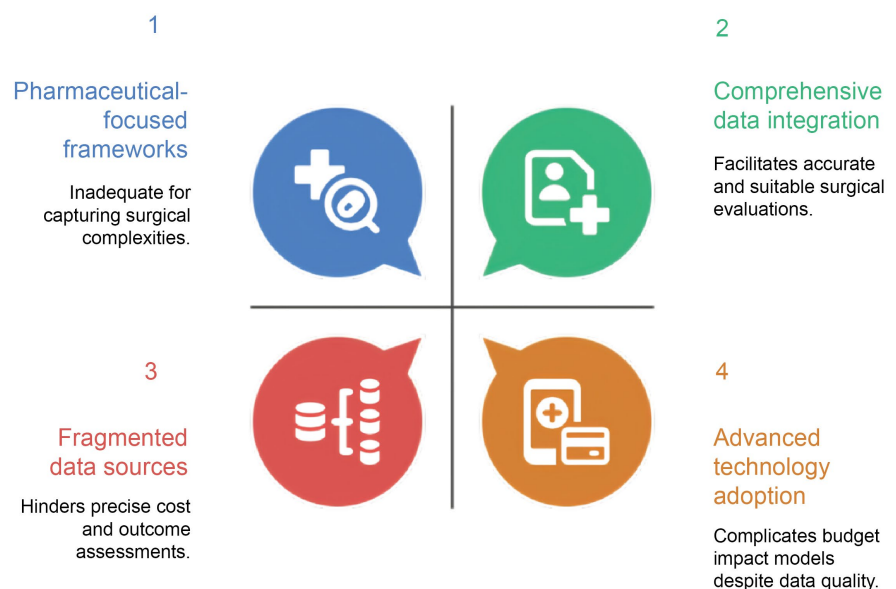
## **3.1. Methodological Limitations**

Surgical cost-effectiveness analyses often rely on frameworks designed for pharmaceutical evaluations, emphasising metrics like Quality-Adjusted Life Years (QALYs) [7]. However, surgical interventions present unique challenges: high upfront costs, delayed realisation of clinical benefits, and complex outcomes that are

difficult to attribute directly to procedural success. Additionally, budget impact models in surgery are complicated by technology adoption curves, learning effects, and variation in institutional capacity [8].

### 3.2. Data Fragmentation and Quality Issues

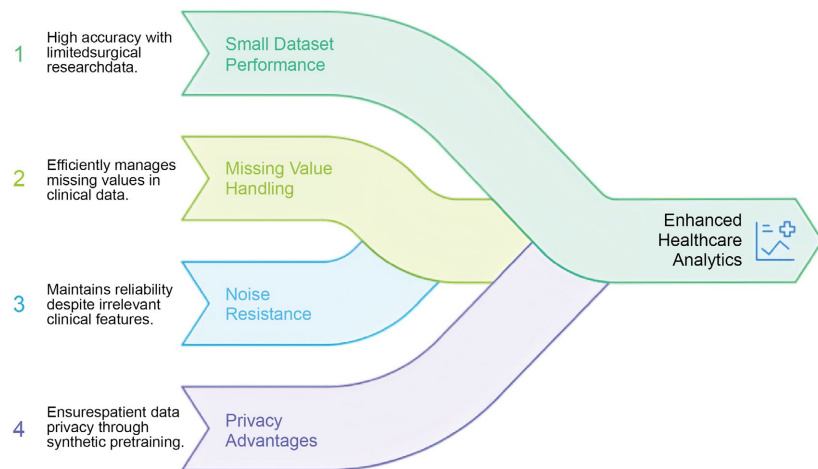
The absence of integrated, comprehensive data sources presents a significant obstacle to robust economic evaluations in surgery. Most databases, whether governmental, commercial, or institutional, capture only partial elements of the care continuum [9]. This fragmentation limits the accuracy of cost calculations, hampers long-term outcome tracking, and often omits essential patient-reported outcomes, all of which are critical to meaningful health economic analysis. **Figure 1** summarises the various challenges faced in surgical health economics research.



**Figure 1.** Challenges in surgical health economics.

## 4. TabPFN's Technical Architecture and Healthcare Advantages

TabPFN represents a foundational shift in tabular data modelling through its use of transformer-based architectures and in-context learning, enabling high performance without task-specific training [10]. As illustrated in **Figure 2**, it addresses several long-standing challenges in healthcare analytics. Comparative evaluations demonstrate that TabPFN achieves predictive accuracies of 3% - 8% higher than leading tree-based models such as XGBoost and LightGBM on benchmark healthcare datasets, while requiring under one second of inference runtime for small- to medium-sized tabular tasks [4] [11]. In contrast, gradient-boosted trees or random forests typically require minutes of tuning and larger sample sizes to achieve comparable performance. These empirical gains substantiate TabPFN's suitability for data-limited and time-sensitive surgical modelling scenarios.



**Figure 2.** TabPFN’s impact on healthcare.

Key advantages include:

- Strong performance on small datasets, particularly relevant in surgical research contexts with limited patient cohorts or rare condition studies [11].
- Native handling of missing values, avoiding the need for imputation and leveraging the informative nature of data absence in clinical settings [12].
- Resistance to irrelevant or noisy features, which enhances reliability in complex and poorly curated clinical datasets.
- Privacy advantages due to its synthetic pretraining, mitigating concerns related to patient-level data exposure [13].

## 5. Transformative Applications in Surgical Health Economics

### 5.1. Precision Health Economic Outcomes Research (P-HEOR)

TabPFN enables patient-level economic modelling that moves beyond average cost-effectiveness metrics. By handling small and heterogeneous datasets effectively, TabPFN supports individualised predictions of cost, outcomes, and value, allowing real-time integration into surgical decision-making processes

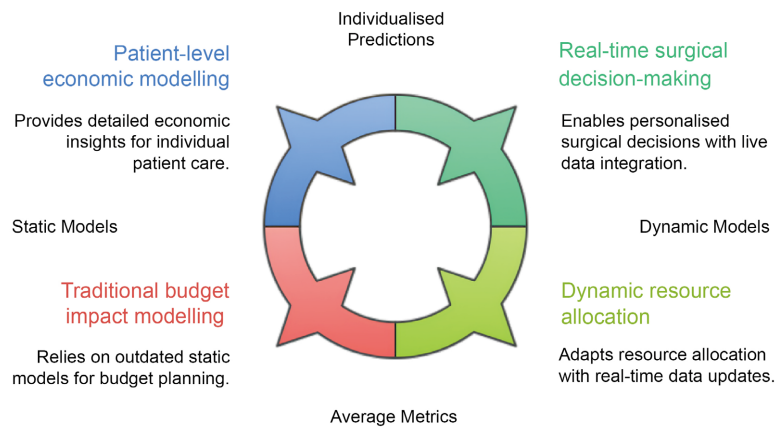
### 5.2. Dynamic Budget Impact Modelling

Traditional BIM approaches rely on static models that are quickly rendered obsolete by clinical or policy changes [14]. TabPFN’s rapid inference and adaptability support dynamic, real-world BIM models that incorporate live data on technology adoption, practice patterns, and institutional variation

### 5.3. Resource Allocation Optimisation

TabPFN can significantly enhance resource prediction and planning in surgical contexts, including operating room scheduling, staff allocation, and postoperative care planning [15]. Current systems often rely on unreliable historical averages; TabPFN allows for real-time, data-driven forecasting. **Figure 3** illustrates the dif-

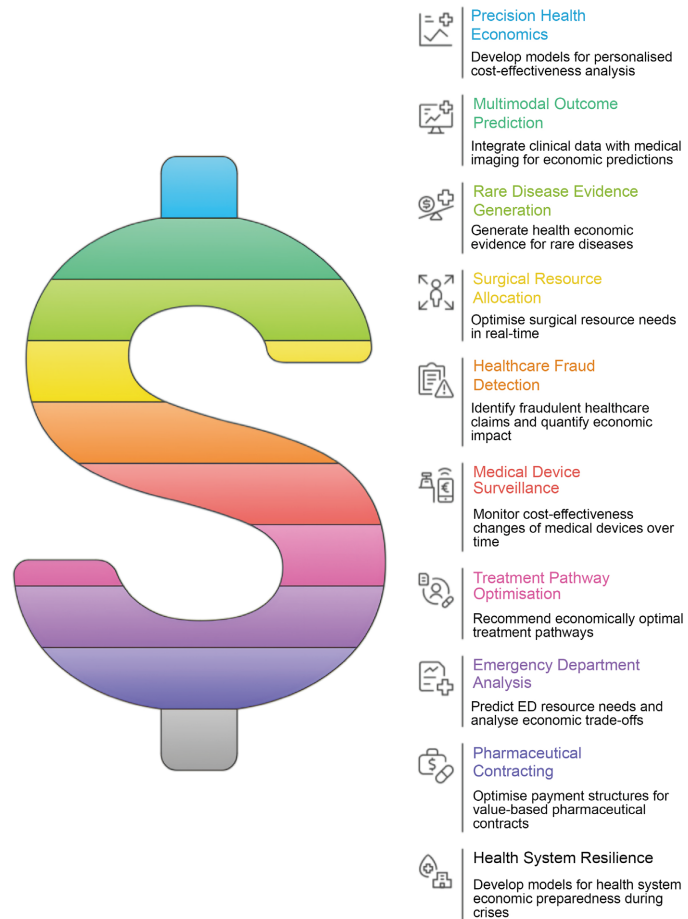
ferent dynamics of TabPFN applications in surgical health economics analysis.



**Figure 3.** TabPFN applications in surgical health economics.

## 6. Future Research Directions

To fully realise TabPFN’s transformative potential, we identify ten priority research areas (as illustrated in **Figure 4**):



**Figure 4.** Maximising TabPFN’s impact in surgical health economics.

- Precision P-HEOR modelling for heterogeneous surgical populations.
- Multimodal economic predictions combining tabular and imaging data.
- Rare disease economic evaluation using small-dataset robustness.
- Real-time surgical resource optimisation tools.
- Economic modelling for healthcare fraud detection.
- Post-market surveillance of medical device economics [16].
- Personalised economic pathway optimisation.
- Emergency Department cost modelling and staffing optimisation.
- Value-based contracting optimisation in pharma contexts [17].
- Health system resilience modelling for crisis planning.

## 7. Technical and Methodological Limitations of TabPFN

TabPFN is still an emerging model with limitations that warrant caution in its incorporation into clinical economic workflows. It is concerning that TabPFN, designed with classifiers in mind, may need further restructuring to be usable for regression outputs, which are predominantly utilised in cost modelling and budget impact analyses [2] [4]. In practice, TabPFN's classification architecture can be adapted for regression by modifying the output layer to predict continuous values rather than discrete class probabilities and by substituting cross-entropy with mean-squared or mean-absolute error loss functions. For instance, when estimating procedure-specific cost distributions, the model can output a continuous cost value per patient episode, enabling simulation of aggregated hospital budget impacts through Monte Carlo sampling. Such adaptation preserves TabPFN's few-shot learning advantages while supporting continuous economic variables. Compared to tree-based models and explainable boosting machines, its interpretability is weaker, which may diminish trust from clinicians or policymakers in multilateral high-stakes decisions [10]. In addition, while lacking the need for extensive retraining is a beneficial feature of TabPFN's zero-shot inference, the competing reduction in task-specific optimisation may limit its usefulness in nuanced or domain-specific applications where predictive granularity is essential [2] [10]. The model's validation on a diverse range of healthcare datasets is sparse, and a thorough evaluation of its robustness to dataset shift, adversarial noise, and variances in data quality triggered by real-world health systems is still lacking [6] [18] [19]. Another potential limitation lies in biases originating from TabPFN's synthetic pre-training data, which may inadequately represent demographic or procedural diversity in surgical populations. This could result in systematic over- or under-estimation of economic parameters for minority or atypical subgroups. A feasible mitigation strategy involves domain-adaptive fine-tuning using small, institution-specific datasets to recalibrate prior distributions, thereby aligning learned representations with real-world surgical characteristics while maintaining generalisability.

## 8. Regulatory and Operational Barriers to Clinical Deployment

The path to deploying TabPFN in clinical environments is not without challenges. Regulatory approval processes remain conservative, focusing on safety and effectiveness rather than innovation [20]. To gain acceptance as an AI/ML-based Software as a Medical Device (SaMD), TabPFN will need to demonstrate transparency, reproducibility, and performance stability under evolving clinical conditions, as expected under frameworks set by the United States Food and Drug Administration (FDA) and the Australian Therapeutic Goods Administration (TGA) [20]. In addition, fragmented healthcare IT infrastructures pose significant barriers to data integration and model interoperability [18]. Despite its low computational demands, TabPFN still requires investment in data quality assurance, governance, and validation protocols to ensure safe and effective implementation [19]. Furthermore, TabPFN's probabilistic output distribution allows derivation of confidence intervals and credible intervals consistent with ISPOR's Good Practice Task Force guidance on uncertainty characterisation in cost-effectiveness analysis [7] [8]. Its capacity for calibrated posterior probability estimation also aligns with FDA's SaMD Action Plan emphasis on transparent uncertainty quantification for adaptive algorithms [20] [21]. Integrating these uncertainty estimates directly into sensitivity analyses and scenario simulations enhances decision robustness and regulatory acceptability.

In the context of public health or clinical decision-making, the use of TabPFN-based tools may require strict adherence to the regulatory framework of Software as a Medical Device (SaMD) as delineated by the FDA or the TGA [20] [21]. Risks associated with the use of machine learning or software incorporated into the decision-making processes for advanced diagnostics, therapy, and management may require evaluation prior to entry into the market, risk classification, and perpetual evaluation even after market entry [22]. As highlighted in the FDA's SaMD action plan, transparency, consistency in performance, and management over time for adaptive algorithms using "Predetermined Change Control Plans" are critical [21]. Correspondingly, the TGA's regulatory guidance emphasises the importance of explainability, traceability, regulation, and the essential element of human oversight for medical technologies based on artificial intelligence [21]. Though TabPFN may not be directly clinically oriented, any integration of systems into a patient's or healthcare institution's economic decision-making systems would demand these requirements to be fulfilled. This underscores the importance of early incorporation of validation frameworks, model explainability frameworks, and use documentation in the translational development of health economic systems based on TabPFN. Thus, the integration of TabPFN in health economic pipelines requires the integration of thorough evaluation frameworks, monitoring strategies post-deployment, and compliance with regulatory frameworks concerning explainability and fairness for AI systems in clinical settings [18] [20].

## 9. Conclusion

TabPFN constitutes a fundamental enhancement in the predictive modelling of surgical health economics. Its design deliberately mitigates the principal shortcomings of conventional methodologies, delivering exceptional performance on small, heterogeneous datasets while simultaneously furnishing robust uncertainty quantification and transparent interpretability. By accommodating personalised cost-effectiveness analyses, iterative budget impact modelling, and real-time resource forecasting, the framework renders analyses once deemed impracticable now commonplace. This capability promises to redefine the practice of health economic evaluation, both at the individual patient level and within broader public health systems, in alignment with the global movement toward precision medicine and asynchronous, evidence-driven clinical decision support. Realising this promise will necessitate synergistic collaboration among computational scientists, surgeons, health economists, regulators, and policy-makers. To fully leverage TabPFN's translational potential, future work must focus on domain-specific validation, SaMD-aligned deployment protocols, and equitable integration across healthcare systems. With these foundations, TabPFN can catalyse a forward-looking paradigm of precision health economics characterised by analytical pre-eminence and tangible clinical and societal value.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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